PRODUCTION NOTES

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Automated identification of intensive animal production locations from aerial photography

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Objective Successful control of an emergency animal disease outbreak requires the timely and accurate identification of properties of interest. The identification of commercial piggeries within study areas in the Goulburn–Murray Irrigation District in Victoria, Australia, is used to demonstrate the innovative application of object-based image analysis (OBIA) techniques for the identification of intensive animal production land uses, to improve the accuracy of existing datasets.

Methods Characteristics of infrastructure and landscape features were combined to form a commercial piggery identification algorithm. These criteria were applied to recent aerial photography that had been classified using OBIA techniques. The results were then compared with three datasets containing known commercial piggery locations and visually checked by roadside surveys.

Results The OBIA technique identified 21 potential piggery locations across three study areas, 14 of which were identified in existing databases. Of the 7 additional sites identified using the OBIA technique, 4 were dairy properties, 1 was a cropping and sheep property and 2 were previously undocumented piggery locations.

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Conclusions The approach successfully demonstrated the potential of OBIA for identifying the locations of commercial piggeries. Further development and testing will determine how generic this approach is in terms of industry type and operation size. The method described is cost-effective, automated and repeatable, and could be used to regularly update existing databases by analysing newly acquired aerial imagery to identify possible land use changes. This would improve the reliability of currently available data and increase the effectiveness of a biosecurity response during an emergency animal disease outbreak.

Keywords biosecurity; commercial piggeries; mapping; object-based image analysis; remote sensing; Victoria

Abbreviations EAD, emergency animal disease; GMID, Goulburn–Murray Irrigation District; MODIS, Moderate Resolution Imaging Spectroradiometer; NLIS, National Livestock Identification System; OBIA, Object-based Image Analysis; PIC, Property Identification Code; RS, remote sensing; VLUIS, Victorian Land Use Information System Geospatial information and mapping are important tools for monitoring animal disease spread and supporting biosecurity responses during an emergency animal disease (EAD) outbreak. The successful control of an animal disease outbreak requires the timely and accurate identification of all properties containing the livestock species of interest. Spatially categorising farms by the animals they contain is also useful for informing land owners of potential risks when outbreaks occur.

Within Victoria, key datasets that hold information about the location of animals and intensive animal production land uses are the Victorian Land Use Information System (VLUIS)¹ and the Property Identification Code (PIC)² database. There are, however, discrepancies and omissions within these datasets that limit their effective use during a biosecurity response. The VLUIS describes land tenure, land use and land cover for each cadastral parcel (locator of geo-information) across Victoria, Australia, based on three main data sources:¹ the Victorian Government Spatial Data Library, Valuer-General Victoria information and land cover information generated from Moderate Resolution Imaging Spectroradiometer (MODIS) satellite imagery.³ VLUIS records one land use per land parcel. Therefore, parcels may have existed where, for example, pigs are present but not considered the main enterprise of the land parcel and consequently not represented in the data.

The National Livestock Identification System (NLIS) is a national system focussed on the identification and subsequent tracing of the movements of individual cattle, sheep and goats within Australia. The NLIS combines a number of elements to enable the lifetime traceability of animals, including the identification of the physical location of a property by means of a PIC, the requirements of which are set out in legislation: the *Livestock Disease Control Act 1994* (Victoria) and *Livestock Disease Control Regulations 2006*. The number of each livestock species on each property with a PIC may be estimated by the number of NLIS-accredited tags or devices sold annually or may be provided by the landowner. Animal species and number information is not verified or updated on a regular or systematic basis and may contain errors.

The main animal production systems currently present in Victoria, such as commercial piggeries, dairy and sheep/beef properties, generally require the use of industry-specific and consistent infrastructure. For example, dairy farms require a dairy shed, a concrete yard attached to the dairy shed, a circular lane adjacent to the dairy shed allowing milk tanker

access and one or more effluent ponds. The identification of such infrastructure and other features specific to various intensive animal production types using remote-sensing (RS) imagery (e.g. aerial photographs) and translation of this onto land cover maps could lead to improved knowledge of the location of these industries. Although the use of RS imagery to provide land cover information is well established, farm infrastructure type is not currently captured within the VLUIIS or PIC database. Use of alternative sources of RS data, with a finer spatial resolution, is needed for this purpose.

RS images store spectral information in pixels. Analysis and classification of such imagery has traditionally focussed on pixel-based approaches. However, utilisation of object approaches (i.e. by analysing groups of pixels) has increased in the recent past, particularly as imagery with fine spatial resolution becomes more accessible. Object-based image analysis (OBIA) approaches are most effective when the spatial resolution of the imagery is finer than the object of interest; for example, when many pixels comprise a building.^{4,5} The spatial arrangement of the pixel group, including shape, structure and pattern, offers information about the object of interest, in addition to individual pixel-based spectral information.⁴ This means that, in addition to confirming the presence of industry-specific infrastructure from RS images, this technique can also be used to highlight the specific dimensions (e.g. length, width) of the infrastructure, allowing the development of identification algorithms based on specific attributes. However, the spatial scale of imagery used in an analysis compared with the size of objects that are to be identified is an important consideration. Jensen and Cowen⁶ suggest the minimum spatial resolution required is one-half the diameter of the smallest object of interest, or a minimum of 4 pixels per object.

OBIA techniques have been used successfully to analyse and model growth and land use change in urban and peri-urban areas,^{7–9} identify and analyse building and road networks,^{10–15} perform ecosystem and landscape analyses,^{16–18} in forestry¹⁹ and agricultural applications,^{20–23} in vegetation^{24–26} and land cover mapping,^{27–29} and to identify features of interest, such as greenhouses.³⁰ However, the application of this technique to the classification of rural land use is considered novel and has not been applied previously to the Australian environment. We describe the innovative application of OBIA to identify industry-specific (i.e. commercial piggeries) intensive animal production infrastructure in the Goulburn–Murray Irrigation District (GMID) of Victoria. The GMID is the largest irrigation district in Victoria, covering more than 894,000 ha. Over 21% of the GMID is estimated to be associated with an intensive animal production land use such as piggeries and dairying. This method and information have the potential to significantly contribute to the effectiveness of a biosecurity response during an EAD outbreak.

Materials and methods

The identification of commercial piggeries within three study areas in the GMID was used to illustrate the application of OBIA for the potential identification of animal production land use. There were four main sections of work involved, as outlined in Figure 1. Characteristics of buildings and other associated features were identified to define that criteria that formed the commercial piggery identification algorithm (Figure 1b). These criteria were then applied, through an automated method (Figure 1c), to recent aerial photography that had been segmented and classified using OBIA techniques (Figure 1a). The results were compared to

existing mapping and visually checked using drive-by surveys to evaluate the accuracy of both the algorithm and its application using OBIA (Figure 1d).

Study area

Three study areas were used to pilot the OBIA approach within the GMID, located near Pyramid Hill, and between Swan Hill and Bendigo (Figure 2). These areas were chosen because they incorporated a number of known commercial piggeries in addition to other intensive animal land uses, such as dairy, and some urban areas. They were identified as (1) Leitchville, (2) Durham Ox East and (3) Mitiamo West.

Data

Aerial photography with a spatial resolution of 18 cm was acquired over the study areas during March 2015. The images were captured as true colour, recording red, green and blue spectral information in 1.8×1.8 km orthophoto tiles. The imagery was georectified to the Geocentric Datum of Australia 1994 datum and VicGrid94 projection, with a horizontal spatial accuracy < 0.4 m. The Durham Ox East, Leitchville and Mitiamo West study areas were covered by 16, 9 and 8 image tiles, respectively.

Three main data sources were collated to provide a complete, 'gold standard' representation of the locations of piggery locations within the study areas: the Victorian PIC database,² the VLUIs¹ and visual digitising of infrastructure based on aerial photography. These data are immediately accessible by the Victorian government during an emergency response.

De-identified PIC data were derived from the PIC database as one source of geospatial data for this pilot study, with the mapping unit existing predominately at the property level.² PIC data included properties where only pigs were located, as well as properties where other animals, such as sheep, horses and dairy cows, were located. A subset of this data was also used in the development of the commercial piggery identification algorithm.

Subsets of the VLUIs dataset were extracted for each intensive animal industry land use category (e.g. piggeries and dairies). The mapping unit was at the parcel level. This dataset only captures one land use per land parcel (i.e. does not allow multiple enterprises to be recorded for a single parcel). A third source of information was derived by manually digitising the extent of intensive animal infrastructure (buildings) from aerial photography to provide an accurate map of intensive animal land use in the GMID. The locations of commercial piggeries identified in this process were checked using the VLUIs and PIC datasets, and were also visually verified on the ground.

OBIA and image classification

Image segmentation and image classification (Figures 1a, 3) were completed using eCognition Developer software v8.7 (Trimble Inc., Munich, Germany) using a multiresolution segmentation algorithm. Within this software, each individual pixel is considered initially to be a separate object. Pixels are then merged to form homogeneous objects based on user-defined parameters, which include a scale factor that is unitless and controls how large the merged regions can become when forming homogeneous objects based on spectral variation; a shape parameter, which determines the importance that object shape is given relative to spectral information in the image; and a compactness parameter, which controls the clustering of pixels within an object and object edge properties.

Following testing of different parameter values, a scale factor of 40, shape parameter of 0.2 and a compactness parameter of 0.7 were used in this study. All three image bands were

given equal weighting. After performing multiresolution segmentation, a spectral difference segmentation was used to combine similar image objects, based on a spectral difference of 7 (Figure 3).

A nearest-neighbour supervised classification algorithm was then used to classify the segmented images (Figure 3). Reference samples were manually identified. The classes used in the classification were cropped paddock/bare ground; cured/sparse vegetation; green vegetation; roof; shadow; bitumen road; unsealed road and water. To assess the accuracy of the OBIA method (Figure 1d), the results obtained were compared with three datasets containing known commercial piggery locations: the PIC database, the VLUIIS, and visual digitisation of the aerial photography. The locations and numbers of known commercial piggeries used to assess the accuracy of the mapped locations identified through OBIA differed from those used to develop the algorithm criteria. Each potential location of a piggery identified by the OBIA technique was also visually checked by roadside surveys to evaluate the results obtained.

Commercial piggery identification algorithm development

To develop the commercial piggery identification algorithm criteria, 55 rural properties located across the GMID were selected and categorised, based on the recorded presence or absence of pigs and other livestock in the PIC database as at 1 January 2016 (Figure 2). The algorithm was developed by analysing the spatial characteristics of features associated with the industry such as buildings (Figure 1b). Property-level categories were applied, based on the recorded presence or absence of pigs and other livestock in the PIC database as at 1 January 2016. The categories used were commercial piggeries (> 100 pigs), pig smallholders (1–100 pigs) and properties containing species other than pigs (i.e. no pigs).

Polygon shapefiles of the selected properties and digital aerial photography were overlaid in ArcGIS 10.3 (ESRI 2016. ArcGIS Desktop: Release 10.3. Redlands, CA, USA:

Environmental Systems). Aerial photography was used to identify all infrastructure on each property, including houses, buildings, silos and tanks. Manual digitising techniques were used to draw around the footprint of each structure, which were added as individual features to a new polygon shapefile and attributed with:

- PIC code
- structure type (e.g. house, building, tank or silo; if it was not possible to distinguish between a building and a silo, they were attributed as building/silo)
- infrastructure length (m): greatest side distance
- infrastructure width (m): shortest side distance
- infrastructure perimeter (m)
- infrastructure area (m²).

Infrastructure length and width were measured on screen using the ArcGIS ‘Measure’ tool. Individual infrastructure perimeter and area were calculated using the ArcGIS ‘Calculate Geometry’ tool. The coordinate system for all measurements in ArcGIS was set to the Geocentric Datum of Australia 1994 datum and the Map Grid of Australia Zone 55 projection.

The data were filtered to include only features identified as buildings and attributes, such as building length, width, area and perimeter, and were visualised using x–y plots in R (RStudio

Team 2016. RStudio: Integrated Development for R. RStudio, Inc., Boston, MA, USA: <http://www.rstudio.com/>).

Mapping commercial piggery locations

The classified images created using the OBIA process were imported into ArcGIS. Image objects classified as roofs, which fitted the commercial piggery identification algorithm criteria, were identified using the ArcGIS 'Select by attributes' and 'Select by location' tools (Figure 1c). The ArcGIS tools 'Buffer' and 'Dissolve' were then used to group the selected roof image objects into clusters within a 200-m radius. These areas were used to highlight the location of a potential commercial piggery.

Results

Commercial piggery identification algorithm

Properties classified as commercial piggeries ($n = 21$) contained between 165 and 30,000 pigs (according to the PIC database), with four properties also containing between 1 and 300 sheep and/or beef cattle. Pig smallholders ($n = 16$) contained a number of other species in addition to between 1 and 23 pigs. On five of these properties the number of pigs present was not recorded, so these were not recorded as commercial piggeries within the PIC or other databases, but instead were classified as pig smallholders for this study. A total of 18 properties were included that only contained species other than pigs, namely dairy cows, beef cattle, sheep, horses and/or poultry.

Based on a visual assessment of x–y plots of several building features (Figure 4), including length, width, area and perimeter, and a number of additional landscape factors, the following criteria were defined to enable identification of commercial piggeries: one or more buildings with a roof length ≥ 40 m and/or one or more buildings with a length/width ratio $\geq 5 : 1$ and a council planning zone group of 'rural', and a distance of at least 15 m from a road (excluding driveways).

The landscape criteria (planning zone and distance from a road) eliminated areas where buildings matching the first two criteria could be found but commercial piggeries logically would not be located such as urban areas.

Testing these criteria using the 55 study properties selected from the PIC database, 76.5% of commercial piggeries where no other species were present on the property were identified as commercial piggeries (Table 1). Overall, 80.9% of the commercial piggeries were correctly identified, with all false-negative classifications applying to smaller commercial piggeries with ≤ 350 pigs (Table 1).

More than 68% of pig smallholders and 88.9% of properties with no recorded pigs were correctly identified as not being a commercial piggery (Table 1). Of those incorrectly identified as a commercial piggery, the predominant species on the farms was dairy cows; two properties contained 146–600 sheep and the remaining two had a small number of other animals or poultry on-farm. Four properties were incorrectly classified based on the presence of one or more buildings with a length ≥ 40 m and two properties were incorrectly classified based on the presence of one or more buildings with a length/width ratio $\geq 5 : 1$. One property had one or more building(s) with both of these features.

Mapping commercial piggery locations using the OBIA technique

Commercial piggery locations were spatially identified using the commercial piggery identification criteria. Figure 5 is a representative result of this process, showing the aerial photography, the land cover map derived from image segmentation and the commercial piggery location identified using the commercial piggery identification criteria. The land cover map (produced using the OBIA method) for the Leitchville study area is shown in Figure 6, identifying the locations of possible commercial piggeries.

Evaluation of the OBIA method

Across the three study areas, 21 potential piggery locations were identified using the OBIA method: 12 in the Leitchville study area, 7 in the Durham Ox East study area and 2 in the Mitiamo West study area; 14 of these piggery locations were listed in existing databases. All piggeries listed in either the VLUIS or PIC databases were identified by the OBIA method. All piggeries mapped from visual digitising of aerial photography were identified using the OBIA method, except for one site in the Leitchville study area. This site was checked in the field and identified as a possible dairy; no animals were observed on the property.

An additional seven piggery locations that were not recorded in either the VLUIS or PIC databases were identified using the OBIA method, and they had not been identified through visual digitisation of aerial photography. Four of these sites were located in the Leitchville study area; three were identified as dairies from roadside surveys, but one was identified as a previously unrecorded pig property. Two of the additional sites were located in the Durham Ox East study area. One of these sites was confirmed in the field as a probable piggery location and the other was a mixed farming property of cropping and sheep. The additional site located in the Mitiamo West study area was identified as a dairy from roadside surveys.

Discussion

Mapping is an important technique for monitoring animal disease spread and informing the direction and scope of biosecurity responses during an EAD outbreak. During a response, the accurate identification of the geospatial location of all properties containing the livestock species of interest within the area of interest is of immediate importance to successfully achieve control of that disease. There are, however, discrepancies and omissions within key Victorian datasets that limit their use in an effective biosecurity response.

Three data sources were used to represent known piggery locations within the study areas and compared with the OBIA results: the Victorian PIC database,² the VLUIS¹ and visual digitising of infrastructure based on aerial photography. Information is also available through industry records such as PigPass, a vendor declaration scheme managed by Australian Pork Limited for the movement of pigs between properties and to abattoirs. To be included in PigPass, a property must have a PIC. Therefore, including PigPass would not have augmented the data already available and was not included in this particular study. The methodology demonstrated here can be used to strengthen these datasets and could potentially be applied, at short notice, during an EAD response. With further development and refinement, the approach could be integrated into existing programs that are used for biosecurity responses in Australia to allow close to real-time, efficient identification of type of land use during an EAD response.

RS imagery has been used extensively to map land cover across landscapes for various applications. Variables derived from RS data, such as land cover and vegetation indices, have been used previously to inform modelling of the geographic distribution of livestock distribution and densities.^{31,32} Typically these have been applied on a gridded or pixel base.^{31,33–35} Utilisation of OBIA approaches has increased in the recent past,^{4,5} as RS imagery with finer spatial resolution has increasingly become available. Although OBIA has been previously used to identify buildings^{7–9} and farm infrastructure such as greenhouses,³⁰ the identification of infrastructure parameters related to specific intensive animal production systems is considered novel and has not been applied to the Australian environment.

Using commercial piggeries as an example industry, this pilot study found that intensive animal production land use may be identified through the novel application of OBIA techniques, as applied to the Victorian rural environment. Comparison of the infrastructure on known commercial piggeries with other types of land use resulted in the development of an algorithm that included industry-specific parameters, such as building length and a width/length ratio. Application of this algorithm, using aerial photos and OBIA techniques, identified known commercial piggeries, while also identifying previously undocumented locations and minimising the number of false-positive classifications.

The case study presented here identified 21 potential commercial piggery locations, 14 of which were identified in existing databases. Of the 7 additional sites identified using the OBIA technique, 2 were previously undocumented piggery locations and 5 were falsely identified as piggeries. The successful application of approaches such as the one presented here depends on being able to identify features that are specific to individual intensive animal production industries and found consistently at different sites of the same industry.

The approach presented here focussed on the identification of larger commercial piggeries to demonstrate the potential of OBIA in this context. Further development and testing of the method will identify how generic this approach is in terms of industry type and operation size. The approach worked well; however, it was less reliable for smaller commercial piggeries. The accuracy of the method is expected to improve over time with the refinement of identifying characteristics and the accumulation of knowledge in this area. OBIA is a useful tool, providing an inventory of features that can be cross-referenced with existing databases and provides a focus for further investigations. This supports a more effective use of resources, particularly in the initial stages of an EAD response.

Future work in this area will focus on improving the sophistication of the algorithms used to identify intensive animal production locations, including consideration of a broader range of industries and identification parameters, which was beyond the scope of this initial pilot study. Key challenges will be the identification of smallholders compared with larger commercial production systems, distinguishing different industries with similar infrastructure requirements (e.g. poultry and pigs), and identifying different types of production within the same industry (e.g. shed-based compared with free-range production).

Identification of different types of production within the same industry and different industry types will require consideration of additional parameters to improve the discriminatory power of the method. The design of the approach allows sets of identification parameters to be

defined and used to identify different industry types or farming styles, which can then be integrated into the overall process workflow.

Different configurations of pig farms, such as smallholder and free-range piggeries, were not considered in the development of this case study. They will have additional or unique identification parameters such as shelter (e.g. huts) in larger open spaces, areas of muddy wallows, ratios of building to open space within a paddock, the configuration and size of feed silos and the presence or availability of water. Factors such as shed roof ventilation (which can be inferred from the mapping by the presence of shadows within a roof object), infrastructure or paddock configuration and the presence of grassy vegetation adjacent to sheds may also assist in discriminating between industries with similar infrastructure (such as piggeries and poultry that both utilise long, thin buildings) or different production systems (such as shed-based and free-range poultry).

Other studies have used variables such as elevation,³⁴ human population³⁴ and vegetation indices³¹ to map intensive animal production land use. Information that may also provide additional discrimination includes infrastructure, such as roads and processing plants, and climatic variables. Future development of this approach will create a more comprehensive set of distinguishing features for different industries and configurations to expand to utility of the approach.

One challenge is to extend this approach to identify potential small 'backyard' holders (e.g. chickens or pigs in a rural residential setting compared with a commercial production setting). Traditionally, these properties are challenging to identify, but are significant during EAD outbreaks, such as foot-and-mouth disease or the highly pathogenic avian influenza. Potential identifying features for these locations are structures such as huts or backyard enclosures on a property with a house, minimum areas of open space and local government planning information or restrictions. An investigation of these factors was beyond the scope of the pilot study presented in this paper, but should be incorporated into future development of this work.

Improvements to the method would also consider the imagery used as a basis for the mapping. Factors such as the time of aerial imagery acquisition during the year, required spatial resolution and the spectral bands recorded should be considered to improve the efficiency of the OBIA method. The temporal currency of aerial photography is another important consideration because this affects the accuracy of the information, what the information is relevant to and also how the information is updated.

Although the pilot study concentrated on a small region, the approach is able to be applied across other areas where appropriate imagery is available and on larger scales such as the state or multiple states. Development of the method would provide scope to tailor algorithms to different regions and incorporate locally specific identifying parameters.

Conclusion

This case study demonstrated that OBIA can be used to accurately identify infrastructure, such as buildings, associated with commercial piggeries. The method presented here identified 21 potential piggery locations, 14 of which had been identified in existing databases. Of the 7 additional sites identified using the OBIA technique, 4 were dairy

properties, 1 was a cropping and sheep property and 2 were previously undocumented piggery locations.

The results supported the potential use of this method as a cost-effective and time-efficient means of identifying potential intensive animal production locations. The success of techniques such as this depends on being able to identify consistent features that are specific to particular intensive animal production industries. The OBIA method could be used to regularly update existing databases by analysing newly acquired aerial imagery to identify possible land use changes in the landscape that require further investigation; that is, newly constructed piggeries and the removal of piggeries from properties. Improved reliability of these data will increase the effectiveness of a biosecurity response during an EAD outbreak.

Conflicts of interest and sources of funding

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Figure 1. Overview of the methodology used to determine commercial piggery locations from aerial imagery using object-based image analysis (OBIA) techniques. The four main sections of the methodology were: (a) OBIA and image classification, (b) commercial piggery identification algorithm, (c) mapping commercial piggery locations, and (d) evaluation of the OBIA method.

Figure 2. Locations of the study properties used to derive the commercial piggery identification algorithm criteria and study areas used to test the algorithm within the Goulburn–Murray Irrigation District.

Figure 3. Overview of the object-based image analysis (OBIA) and image classification process.

Figure 4. Individual building length (m) versus the ratio of building length/width, by property category (commercial piggery = circle; smallholder = Square; other species = triangle). Buildings classified as belonging to a commercial piggery, based on the two criteria, are black (commercial piggery) or grey (smallholders and other species). Buildings that were not identified as commercial piggeries, based on the two criteria, are shown as white.

Figure 5. An example of the process used to identify a commercial piggery using object-based image analysis (OBIA): (a) aerial imagery, (b) land cover classification derived using OBIA and (c) land cover classification with the potential piggery location identified using the commercial piggery identification algorithm.

Figure 6. Land cover map derived from the object-based image analysis (OBIA) process showing potential piggery locations within the Leitchville study area (Goulburn–Murray Irrigation District, Victoria, Australia).

Table 1. Summary of the number (%) of properties correctly identified, by category, using either building length or a length/width building ratio, and the use of a specific parameter to correctly or incorrectly identify a property as a commercial piggery

Property category	n	No. (%) of property category correctly identified	No. of properties identified as a commercial piggery	
			Based on building length ≥ 40 m	Based on building length/ width ratio $\geq 5 : 1$
Commercial piggery (no other species)	17	13 (76.5)	13	7
Commercial piggery (other species present)	4	4 (100.0)	3	3
Pig smallholder (other species present)	16	11 (68.8)	3	2
No pigs, only other species	18	16 (88.9)	2	1

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