



1 **Semi-automated roadside image data collection**

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6

7 **Abstract.**

8 This article describes the development of a mobile roadside survey procedure for obtaining corroboration
9 data for the remote sensing of agricultural land use practices. The key objective was to produce a dataset of
10 geo-referenced roadside digital images that can be used to compare to in-field photos for measuring
11 agricultural land use and land cover associated with crop residue and cover cropping in the non-growing
12 season. It was concluded that a very high level of correspondence (>90% level of agreement) could be
13 attained using a mobile survey vehicle, as presented in this research, to detailed in-field ground verification
14 data. Classification correspondence was carried out against 114 field sites with a level of agreement at
15 93%. The few discrepancies were in the differentiation of residue levels between 30-60% and >60%, both
16 of which may be considered as achieving conservation practice standards. The mobile roadside image
17 capture has advantages of relatively low cost and insensitivity to cloudy days, which often limits optical
18 remote sensing acquisitions during the study period of interest. We anticipate that this approach can be used
19 to reduce associated field costs for ground surveys, while expanding coverage areas and may be of interest
20 to industry, academic and government organizations for more routine surveys of agricultural soil cover
21 during periods of seasonal cloud cover.

22 **Introduction**

23 The identification and verification of in-field characteristics is an inherent component of the remote sensing
24 of land use and land cover (LULC), and change detection classifications for the assessment of post-harvest
25 tillage and cover crop practices (Hussain, *et al.*, 2013). Traditionally, the generation of training and
26 evaluation data sets for remote sensing classification approaches rely on in-field physical measures that
27 include both nadir and oblique image capture, physical counts of residue to bare earth percentages over a
28 series of 3 - 5 geo-referenced sample plots to represent a satellite pixel (e.g. Pacheco and McNairn, 2010;
29 AAFC, 2011; Laamrani *et al.* 2017). Such methods, while effective in the categorization of crop residue
30 classes for research purposes, are costly, labour intensive, and limited logistically to characterize a large



1 region, such as at the county level, in quantifying annual tillage and cover crop use and trends. These
2 methods are also inefficient for situations when generalized classes of landcover are sufficient for program
3 and policy decision making activities.

4

5 The common post-harvest activities used in agriculture land management in the southern Ontario study
6 region include conventional (CV), conservation (CS) and no tillage (NT), and potentially cover cropping
7 practices; defined as follows. Conventional tillage is a common post-harvest practice for many large-scale
8 agricultural operations. This tillage practice involves incorporating, or turning residual plant matter into the
9 soil following harvest, and with additional seedbed preparation prior to the following planting cycle.
10 Conventional tillage is effective at controlling weeds, however, the burial of residue, and the increased
11 disaggregation of the soil encourages runoff and erosion (Moreira *et al.*, 2016; Dam *et al.*, 2005). This
12 practice also leads to an increase in carbon release to the atmosphere via accelerated organic soil matter
13 breakdown, which has been linked to climate change (Silva-Olaya *et al.*, 2013). Aside from these issues is
14 the cost in time and fuel (if using mechanized tools – e.g. tractors) of repeated passes over the field.
15 Conservation tillage (CS) and No-tillage (NT) use implements designed to limit soil disturbance to reduce
16 surface disruption, and leave a protective organic layer (crop residue) between harvest and subsequent
17 plantings (Steiner, 2002). The difference between CS and NT residue classes lie in the amount of material
18 left between harvest and replanting on the surface, where CS residue is typically classified with residue
19 coverage between 30 and 60 percent, and NT categorization having in excess to 60 percent, as opposed to
20 residue cover significantly less than 30 percent for conventional (CV) practices. Both CS and NT practices
21 have been shown to influence soil microbial biomass (Mathew, *et al.*, 2012; Govaerts *et al.*, 2007;
22 Spedding *et al.*, 2004) and hydraulic properties (Blanco-Canqui *et al.*, 2017; Gozubuyuk *et al.*, 2014) by
23 improving soil quality via an increase in soil organic matter (Daughtry and Hunt, 2008). Both methods
24 reduce soil disturbance, compared to conventional methods, and therefore assist in carbon sequestration
25 (Dolan *et al.*, 2006; Halvorson *et al.*, 2002; Angers *et al.*, 1997). Maintaining large amounts of non-
26 photosynthetic plant material on the surface, no-till practices somewhat mimic a natural ecosystem scenario
27 (Jabro *et al.*, 2016; Arshad *et al.*, 1999). The added layer of plant material, however, can trap moisture and
28 create a fertile environment for both fungal and weed development (Govaerts *et al.*, 2007).

29

30 Another practice employed after crop harvest is to establish a living plant green cover. In this study, green
31 cover in fields included fields planted to perennial crops (i.e. predominantly alfalfa or alfalfa/grass
32 mixtures), winter cereals (i.e. winter wheat predominantly) as well as cover crops (e.g. Oats, oilseed radish,
33 clover). The green cover secures the inverted soil against wind erosion and maintain moisture levels and



1 material for decomposition prior to spring planting. Green cover species with deep tap roots can be
2 important to breaking through compacted layers and may be considered a fourth tillage practice (Derpsch,
3 2003). If green cover can get established early enough that there is significant cover of the soil, it can
4 effectively dissipate direct rainfall striking the soil surface promoting diffuse infiltration and limiting
5 potential for surface runoff and erosion.

6

7 As of 2009, Agriculture and Agri-Food Canada (AAFC) implemented a crop inventory database in Canada
8 using satellite remote sensing data and ground-based verification (Fisette *et al.*, 2014). While orbital, or
9 high altitude aerial remote sensing is routinely employed for land-use classification, optical remote sensing
10 methods are limited by opaque atmospheres (Thoma, *et al.*, 2004) as regularly present in both the spring -
11 pre-planting; and in fall, post-harvest. While Radar remote sensing has been utilized to circumnavigate
12 such issues, there are remaining issues in the collection of ground data to develop wider-scale
13 implementation of remote sensing classification approaches for non-growing season land management
14 practices. Planning field verification missions, being costly from a personnel and travel perspective, can be
15 minimized using single vehicle large scale surveys, which function equally well in clear or overcast
16 conditions. Roadside surveys, however, primarily focus on oblique horizontal/ landscape data capture, as
17 opposed to vertical nadir views afforded by most high altitude airborne and orbital platforms.

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19 An issue prevalent in using oblique photography for landscape evaluation lies in the variable scale inherent
20 in such images as function of image tilt, focal length, sensor resolution, and camera height (Remondino and
21 Gerke, 2015). Subsequently, the background image pixels are representative of a larger geographic area
22 than their foreground counterparts, and effective quantification of surface variation is limited to relative,
23 rather than absolute measures (Stockdale, *et al.*, 2015). For generally homogeneous landscape
24 categorization, however, especially if being used for the generation of ground-truth training sites against
25 nadir-view high altitude aircraft or satellite remote sensing classification, such methods are suitable for
26 rapid ground class assessment. The virtue in oblique imagery lies in its simplicity of interpretation and
27 understanding, being the way in which we are accustomed to viewing the world (Remondino and Gerke,
28 2015).

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30 The objective of this study was to establish a baseline percentage of Ontario county level agriculture fields
31 employing different tillage practices through the development, and testing of a ground survey data, vehicle-
32 mounted, camera system. The survey system was developed to compare to in-field photos for measuring
33 soil cover in order to determine the value of roadside acquisition for both routine ground truth data



1 collection for remote sensing analysis of soil cover, and the utility of using such data collection as a
2 surrogate to standard practices which are reliant on orbital remote sensing classification.

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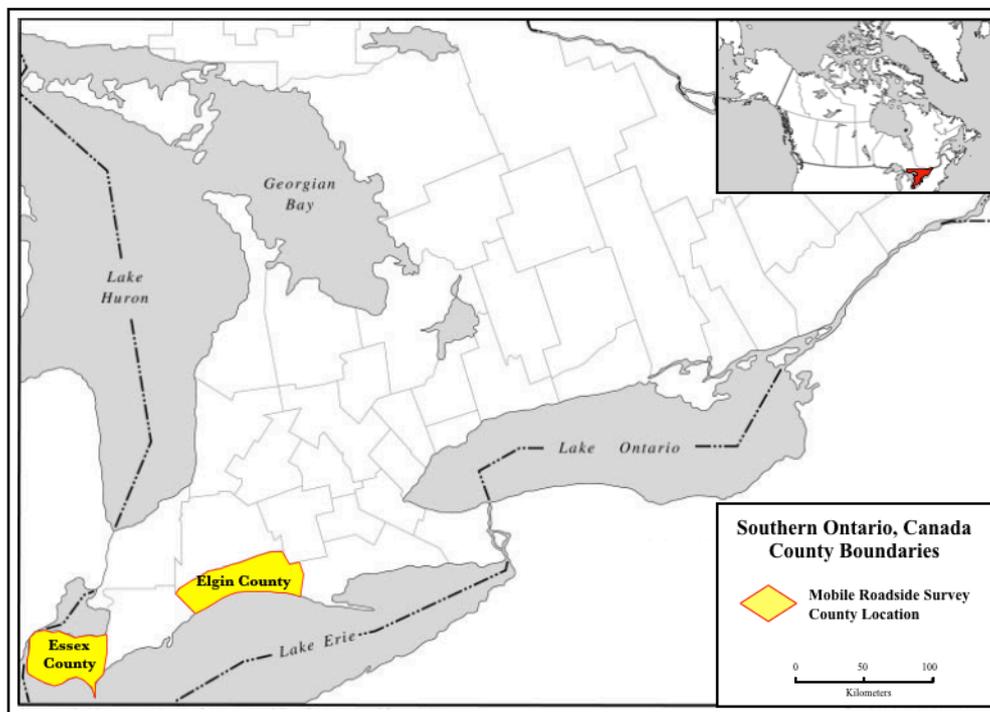
4 **Methodology**

5 **Site Location**

6 Fieldwork was conducted in Elgin and Essex county in South-western Ontario, Canada (Figure 1).
7 Dominant crops in these areas include corn (*Zea mays*), and soybean (*Glycine max*), and winter wheat
8 (*Triticum aestivum L.*) grown in rotation, interspersed occasionally with perennial forages. As discussed
9 above, various practices are followed after harvest including use of cover crops, conventional, CT and NT,
10 resulting in different soil surface cover conditions during the non-growing season.

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Figure 1. Map of roadside survey area locations.



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2 **Instrumentation**

3 The vehicle mounted road side imagery system (Figure 2) included a pair of Garmin VIRB XE cameras
4 and a full-spectrum (near-infrared) modified GoPro HERO camera. The imaging systems were mounted
5 perpendicular to the vehicles travel direction, extended above permanent mounting brackets to an elevation
6 of 2.3m (7.5') on the right (curb-side) and up to 2.6m (8.5') on the left (driver-side) above ground level to
7 compensate for the additional distance to drivers-side fields. The extension poles were further reinforced
8 against vibration using foam insulated cable ties to roof rails, and support mounts on the vehicle. A large
9 proportion of the driving route for each county was comprised of rough gravel, or packed dirt roads; hence
10 a 4WD with a modified soft suspension was required to reduce vibration on the imaging platforms
11 themselves. Further the 4WD vehicle with its higher ground clearance allowed for higher mounting of the
12 side-looking cameras.

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15 **Figure 2. Roadside survey vehicle camera system with roof-top camera mounts**

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18 Data collection for Essex and Elgin County were carried out on May 18, and 20, 2016, respectively under
19 clear sky conditions. Acquisition plans were conducted to coincide with Landsat 8 OLI overpass and the
20 concurrent in-field ground-truth data collection for each respective area. Data collection was carried out in
21 this manner to produce a value-added product that could be employed for ground-truth evaluation of future
22 studies employing the Landsat orbital platform. Thus, permitting additional use for the collected imagery in



1 a secondary land-use study not covered in this pilot experiment.

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Table 1. Weather and sky conditions during the two roadside image acquisitions.

Location	Essex County	Elgin County
Date	2016-05-18	2016-05-20
Route Distance	102 km	248 km
Mean Temperature	12 C	14 C
Sky Conditions	mostly clear	mostly clear
Visibility	unlimited	unlimited
Pressure	1021.92 hPa	1023.07 hPa

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7 **Driving Parameters**

8 Route maps were designed for the two sampling locations to minimize overlap in image acquisition, and to
9 ensure adequate coverage of AAFC field plots for comparison between mobile collected, and in-field static
10 image capture and residue quantification (Appendix A). Driving speed was maintained between 40-45
11 km/h to ensure image capture of every field with shutter actuation on each camera set at 5-second intervals.
12 Following a previous field survey in Elgin County on 2016-05-11, it was determined that a reduced driving
13 speed be implemented to reduce vibration through the vehicle to the elevated camera platforms. Therefore,
14 a speed restriction of 40-45 km/hr. was used on the subsequent (Essex and Elgin County – 2016.05.18,
15 2016.05.20, respectively) acquisitions.

16

17 Driving speed and shutter actuation are inherently related, and based on average roadside field dimensions.
18 The following equation was used to calibrate both shutter actuation and driving speed.

19

$$20 \quad SA = DS \text{ (m/sec)} / (\text{MFW (m)}/3) \quad \text{(Equation 1)}$$

21

22 Where SA = shutter actuation interval in seconds; DS = vehicle driving speed in metres per second; MFW
23 = mean field width in metres, based on pre-site planning of field polygon network for each respective
24 sample area. This value is then divided by 3 to ensure a minimum of 2 usable images for each respective
25 field. Multiple field image captures are required in event that undesired features (people, vehicles, trees,
26 etc.) are visible at the forefront of the imaging plane.



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2 **Data Processing**

3 **Data Transfer and Sorting**

4 Following each site acquisition, image files were transferred to a desktop computer for sorting. A total of
5 18,462 images were acquired for the 2 routes. The images were manually sorted by site, date, and look
6 direction for the particular camera whereby any images not meeting the requirements of the project were
7 subsequently deleted. Examples of deleted scenes include images of forests, houses, quarries, intersections,
8 overpasses, non-agricultural structures, road-vehicles, or any that contained identifiable footage of
9 individuals.

10 **Geometric Rectification**

11 An issue prevalent with wide-angle oblique image capture is the so-called fish-eye, or barrel effect. The
12 geometric distortion in the radial direction, while present in all aspects away from the centroid of the
13 imaging plane, results from compression in peripheral regions allowing for a wide-angle view to be
14 presented in the image plane (Kim and Pail, 2015). Such distortion presents issues in many land-use studies
15 by virtue of a variable pixel-to-ground scale across the image plane, and the removal of lens distortion is
16 often preferred in multi-class image classification, especially where volumetric measures of scene features
17 are required (Chow, *et al.*, 2018; Stockdale, *et al.*, 2015). While not absolutely pertinent to this land-use
18 study, image correction was performed using Liquivid© Video Fisheye Removal software; other open-
19 source image correction software, such as Mathmap:GIMP; GML Undistorter; RadCor; Photivio;
20 FisheyeGL, among others (listoffreeware.com, 2019) are also readily available for the correction of wide
21 angle lens distortion. The correction permits cross platform image sharing for a subsequent study where
22 geometrically rectified imagery is required.

23 **Coordinate Encoding and Verification**

24 The GPS vehicle mounted cameras include horizontal geographic lat/long coordinate information in
25 addition to other variables including, elevation, slope and aspect that are transferrable to the imagery via
26 still-to-video image conversion. Transfer of ancillary information to coordinate geometry was performed by
27 creating a stop-motion video comprised of the 4 sorted, and geometrically rectified image data-sets (left
28 and right for 2 acquisitions), then deconstructing the video back to individual static images. The process
29 allowed for extraction of coordinate coding for each image and the generation of a point for each image
30 location to be displayed in a GIS environment. In this instance we used ESRI ArcGIS, however the same



1 methodology may equally be employed using many open source alternatives (e.g. GRASS, WhiteBox,
2 QGIS, uDIG, etc).

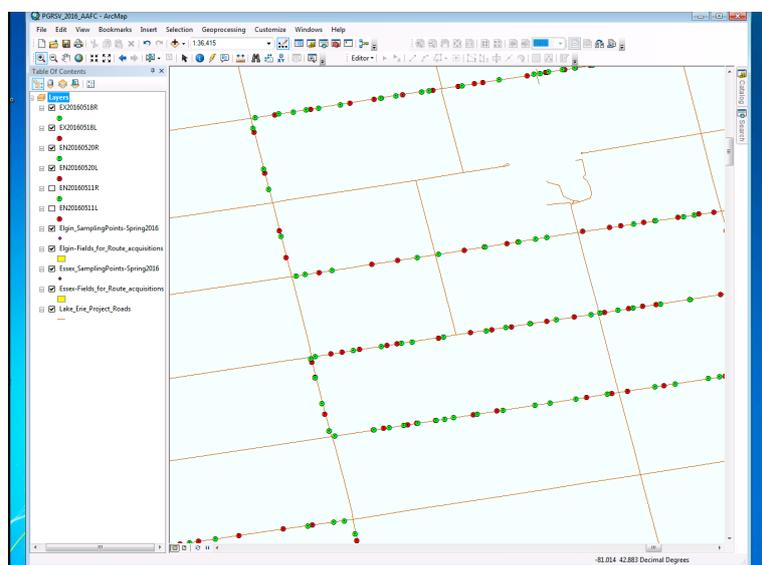
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4 **GIS Integration and Map Overlay**

5 **Geodatabase creation**

6 A geodatabase of the imagery was created within an ESRI ArcGIS 10.1 environment. The roadside images
7 were linked to a point feature class layer for spatial identification based on the inherent coordinate data
8 captured coincident with the roadside imagery (Figure 3). Determining the point feature classes were then
9 linked to individual field polygons to allow for photo identification of each field within the study region.
10 This procedure allows the user to zoom in to each field location and visually assess any roadside images
11 connected to the given field polygon (Figure 4).

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14 **Figure 3. Geo-referenced roadside survey image locations. Green = right viewing, Red = left viewing to vehicle**
15 **forward movement. Direction of movement determined by imbedded time-stamp of subsequent left or right**
16 **geo-referenced points.**

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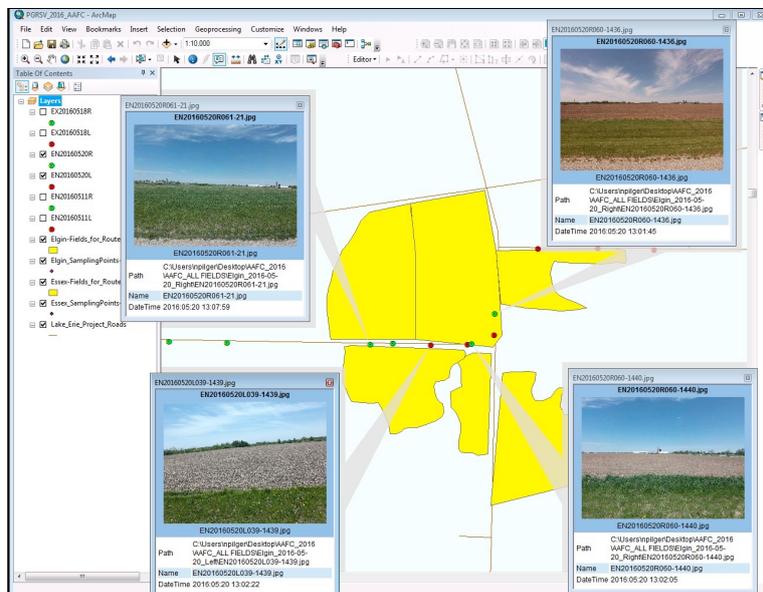


Figure 4. Hyperlinked image files to point and field polygon network.

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A benefit of this procedure is the ease of updating visual examples of each respective field in a given area, and the immediate comparison to changes in both crop type and tillage practices. The technique is adaptable to be carried out over a series of years, while minimizing the time and costs to be physically present in the reference, or validation fields themselves. Images captured by field research were assessed by OMAFRA staff trained in conducting visual surveys to belong to one of 5 to 6 residue classes, which were then rescaled into the 4 cover classes (Figure 5) to be used in validating the oblique mobile image capture.

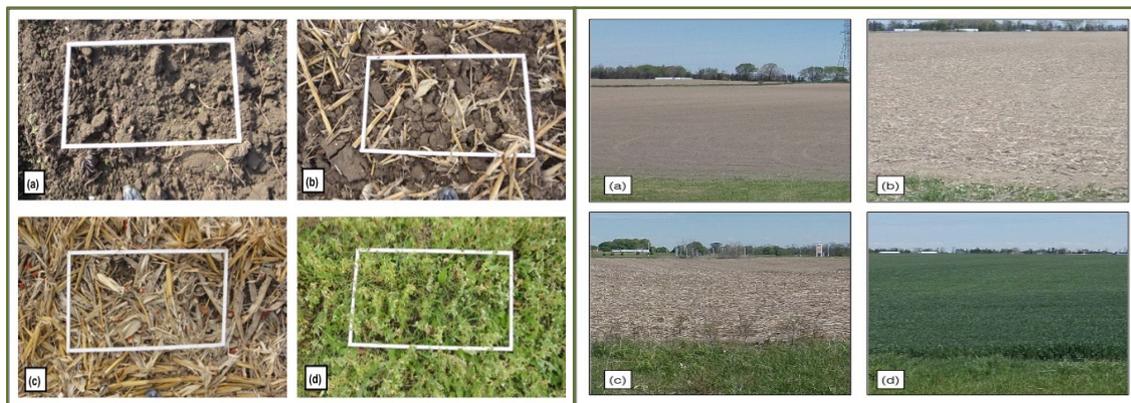


Figure 5. Classes as recorded using in-field, and roadside survey. (a) Conventional; (b) Conservation; (c) No-Till; and (d) Green Cover.

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1 Ground-based validation of roadside image capture was performed using data from 114 research sites
2 across the two counties collected by AAFC scientists coincident with roadside image capture. The in-field
3 research sites were evaluated for residue percentage using a photo-grid sampling technique where average
4 counts were derived from random selections on three digital images captured at 90 degrees from surface
5 normal, or nadir view over 0.75 x 1.0 meter survey quadrats. Residue and green cover counts of the photos
6 were performed using of 10 x 10 digital grids, representing 100 points for each imaging frame (Laamrani,
7 *et al.*, 2017, 2018), where cover percentage was based on presence or absence over each of the 100 grid
8 intersection points and categorized as conventional (0% - 30%); Conservation (30% - 60%); and No-Till
9 (60% - 100%) residue (figure 6). The green cover class was assigned when >90% field was visually
10 composed of green, actively photosynthesizing vegetation.

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Figure 6. Superimposed 10 x10 photo grid over corn residue field sample quadrant.

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29 This digital method of in-field residue evaluation was found to be highly correlated to traditional line
30 transect methods to accurately estimate post-harvest residue percentages, but in a more efficient manner
31 (Laamrani *et al.*, 2017).

32

33 **Results**

34 A confusion matrix (Table 2) was used to compare the mobile roadside imagery classes against in-field
35 collected data classes (Figure 5) for the 114 research sites distributed over the two counties surveyed during
36 this research project. While overall agreement between roadside collected imagery (RS) and in-field (IF)



1 measures was strong, there are some minor areas of confusion, primarily between conservation (CS) and
 2 no-till (NT) fields. This may be explained by the visual similarity at distance from the roadside between
 3 these two land-classes (Figure 5 b and c (right side)).

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6 **Table 2. Error matrix mobile roadside (RS) oblique vs ground collected nadir in-field (IF) imagery, for**
 7 **conventional tillage (CV); conservation tillage (CS); no-till (NT); and green cover (GC) practices. Validation**
 8 **carried out against 114 AAFC field sites in Elgin and Essex County. Omission and Commission error values**
 9 **for each land class are reported in the last row and column respectively, with an overall accuracy of 93%.**

10

<i>n</i> = 114	IF-CV	IF-CS	IF-NT	IF-GC	Total	Error
RS-CV	30	1	0	0	31	3.2%
RS-CS	0	21	5	0	26	19.2%
RS-NT	0	2	37	0	39	5.1%
RS-GC	0	0	0	18	18	0%
Total	30	24	42	18		
Error	0%	12.5%	11.9%	0%		OA= 93%

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13 Another issue relating to confusion between the tillage classes involves the look direction variation
 14 between nadir and oblique image capture. For example, a harvested field of corn will appear to contain
 15 higher levels of residue in an oblique image, as we are viewing the residue from the side, and overlap
 16 occurs as a function of perspective, whereas in a nadir view a greater proportion of bare soil will be visible
 17 within the image. As both Conservation and No-Till meet thresholds representative of conservation
 18 methods (i.e. >30% cover for soil erosion protection), the misclassification between the two is deemed
 19 acceptable in this case.

20

21 **Challenges and Environment**

22 While few, there are a number of challenges that must be addressed in carrying out an operation of this
 23 scope. These will be addressed in order of technological importance. Weather, is paramount if requiring
 24 coincident optical satellite imagery with field interpretations; besides this requirement, for roadside data
 25 collection the following are the key challenges to overcome.



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2 Driving speed: technically higher speeds should lead to a blurring effect on short distance image capture.
3 This is especially true when light levels are low. However, in comparative tests following all acquisitions,
4 shots captures at 40 km/hr in bright clear atmospheric conditions were only marginally sharper than those
5 captured at 60 km/hr + during overcast conditions. The real benefit of a reduced driving speed, therefore,
6 lies in a reduction of vibration from wheel-base through to camera mount.

7

8 Wind speed: as with vehicular velocity above, higher wind speeds increase vibration through the vehicle
9 and the extended camera mounts. Vibration can significantly affect image clarity and subsequent
10 assessments. From this pilot project there is evidence in image capture footage where heavy gusts can also
11 offset the horizontal plane of the camera. While efforts were in place to minimize such effects (insulated,
12 damping core wire ties from cameras and extension poles to vehicle roof-rails) excessive gusting can affect
13 the horizontal image plane.

14

15 Shutter actuation: Shutter actuation, is intrinsically linked to driving speed, and external light conditions.
16 While one could capture images at up to 10 shots/sec. the associated image sorting time required if
17 conducted manually as in this project would render such operation financially unsound. Setting camera
18 aperture to ensure that every field is captured a minimum of 3 times in a pass required pre-assessment of
19 field orientation, and dimensions as this will vary by the land survey system by geography. This enabled
20 calculation of maximum driving speed (in this case it varied between 30-50 km/hr) with a 3-5 second
21 actuation interval.

22

23 Privacy concerns: Though listed last, privacy concerns are paramount in post production though not a
24 technical issue. Any images where people, especially children; vehicles; homes; etc. are visible and
25 identifiable have potential to raise privacy concerns and cannot legally be distributed through any
26 commercial or government shared channels. With a sound editing and sorting methodology, any such
27 images would be deleted in an expedient manner, following a best practice protocol.

28

29 **Conclusions**

30 Key benefits of the mobile ground-based reference data collection method described in this paper are the
31 flexibility garnered through not requiring any specific meteorological conditions, as is the case with most
32 optical airborne, and orbital platforms; enhanced safety by removing manual real-time roadside
33 classification, and driver distraction by incorporating an automatic imaging system.; and creating archival



1 footage on land and lands conditions for future reference. Temporally, collection dates are limited in tillage
2 assessment studies carried out in temperate climates. Ground-truth imagery is required with in the late
3 autumn, prior to snowfall; or in late spring, following snowmelt, but prior to any seedbed preparation
4 practices carried out prior to planting. In southwestern Ontario, skies are generally overcast for the majority
5 of days in these narrow temporal windows, thus limiting traditional classification using orbital, or high
6 altitude airborne image capture. Specific fields that have not been harvested at the time of roadside image
7 capture, may readily be re-visited, or such field-data may be in-filled at a later date, either via direct contact
8 with land holders, or through other citizen provided reference data (Foody, 2015). Mounted with opposing
9 side viewing cameras, the roadside survey vehicle was shown to be highly efficient in the collection of geo-
10 referenced imagery of up to 500 fields per hour, with an overall level of agreement to in-field ground
11 surveys at 93 percent, employing a single vehicle, and 1-2 operators, producing a more reliable and robust
12 data-set for extrapolation to larger areas, compared to the 5 to 10 fields which could be surveyed in the
13 same time frame using conventional in-field methods.

14 Another benefit is that time series of these surveys would permit change detection analysis over subsequent
15 years to evaluate climate adaptations, routine monitoring for productivity, soil surveys and yield estimates
16 (Fisette, *et al.*, 2014, Kennedy, *et al.*, 2009); to determine impacts of regulations that may result in the
17 adoption of particular cropping practices in the province (Vercammen, 2011); and to inform recommended
18 methodologies that can be used by industry, provincial or federal organizations for more routine
19 measurement of soil cover.

20

21 This project demonstrated that this method can provide rapid determination and dissemination of post-
22 harvest tillage and green cover practices over county level areas even where atmospheric conditions are
23 unfavourable for satellite remote sensing, while improving on financial, temporal, and safety costs for in-
24 field verification data acquisition.

25

26 While this study focused on the resource-based utility of employing mobile roadside image capture for use
27 in characterizing post-harvest field conditions, a follow-up project is underway to investigate residue
28 decomposition rates and subsequent field operations to determine optimal timing in such mobile field
29 surveys. Also, based on date of image capture, some fields showed evidence of recent soil turning,
30 therefore the fields analyzed may indicate higher levels of soil disturbance being classed as conventional
31 tillage than what may in fact be a conservation practice carried out by the landowner. In this respect, one
32 must take into account the temporal influence of any tillage residue survey. With many agricultural surveys



1 being carried out coincident with satellite overpass, potential classification errors, as described in this
2 manuscript, stress the benefit of a non-orbital dependent classification technique.

3

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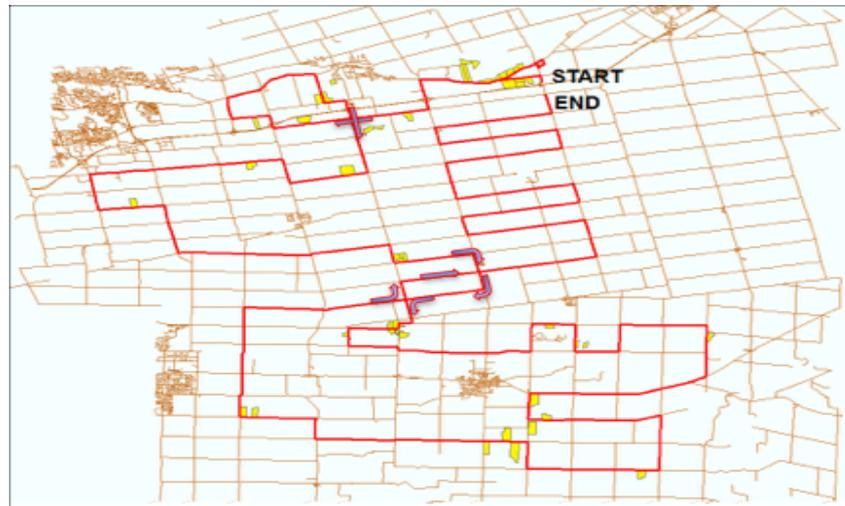
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1
2
3 **Appendix A.**
4



5
6 Figure A1. Essex County driving route map. AAFC fields denoted in yellow.
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10 Figure A2. Elgin County driving route map. AAFC fields denoted in yellow.