OPPORTUNITIES AND LIMITATIONS OF REMOTE SENSING FOR CROP LOSS (HAIL DAMAGE) ASSESSMENT IN THE INSURANCE INDUSTRY

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ABSTRACT

Crop loss assessment in the insurance industry should be conducted efficiently, cost effectively and accurately. While crop loss adjusters in Australia have been implementing their own crop assessing systems with acceptable success, the use of remote sensing imagery offers potential to enhance the current systems. Our project aimed to: a) assess the relationship between crop defoliation and spectral data, and to b) identify the situations or conditions where contemporary remotely sensed imagery can be used in assessing crop loss due to hailstorm.

A hand-held spectrometer was used over sites in the Darling Downs region, Queensland on: a) trial plots with simulated hail damage on corn, and on b) young sorghum crops damaged by hailstorm on 2 December 2004. Landsat and SPOT images were used on post-flowering sorghum crops hit by hailstorm on 1 February 2004. To analyse the relationship between defoliation and spectral data, correlation analyses and partial least squares (PLS) regression were conducted for the three sites. For the second objective, a 2-day workshop involving experts in the industry was conducted.

The results indicated that defoliation and spectral data from Landsat and SPOT imagery are highly correlated (r = -.91 and r = -.93, respectively). However, for the hand-held spectrometer data, the correlations were variable over the two sites (i.e. r = .71 and r = -.40). Overall, the regression results indicated that the spectral data are good predictors of defoliation, with accuracy ranging from 81% to 85%. However, despite the potential, the effects of confounding factors can render the regression models less acceptable for the insurance industry. Consequently, remote sensing can be used in a supportive role (e.g. targeting of areas for priority deployment of field assessors) and as a cost-saving tool to rationalise field sampling strategies. Future work should focus on how to restrict or isolate the effects of confounding factors during estimation.

BIOGRAPHY OF PRESENTER

Armando A. Apan received the BSc degree in forestry from the University of the Philippines, the MSc degree in natural resource management from the Asian Institute of Technology, Thailand, and the PhD degree in Geography from Monash University, Melbourne, Australia. He is currently a Senior Lecturer with the Faculty of Engineering and Surveying, University of Southern Queensland, Toowoomba. His current research area focuses on the use of hyperspectral remote sensing, field spectroscopy, and GIS for mapping and monitoring agricultural crops and forest vegetation.

INTRODUCTION
Hail can cause serious damage to agricultural crops. In the Darling Downs region of Queensland, Australia, millions of dollars of production (approximately 3% of the total cereal crop production) is lost every year due to hail damage [Chandler, 2001]. In response to the prospect of hail, many farmers protect themselves against crop failures due to hailstorm by purchasing crop insurance cover. When a hail event occurred and a claim was lodged by the insured, third-party crop loss adjusters determine the amount of crop loss.

Traditional crop hail loss assessment is time-consuming and very labour-intensive [Peters, et al., 2000, Chandler, 2001]. Various limitations have also been identified to exist with the current systems of loss assessment, such as difficulty to provide accurate and reliable analysis, variability of assessment results between adjusters, difficulty to view the entire area due to size or access constraints, and difficulty to gain access to the property due to uncontrollable factors [Chandler, et al., 2002].

While crop loss adjusters in Australia have been implementing their own crop assessing systems with acceptable success, there are opportunities to enhance the current systems. One of these opportunities is the use of remote sensing technology, which has the potential to reduce loss assessment costs and accelerate claims processing [Swiss Reinsurance Company, 2002]. The use of imagery and digital image processing techniques can provide alternative methods for the assessment of crop hail damage.

To help in establishing the feasibility of using remote sensing technology to crop assessment, our project aimed to: a) assess the relationship between crop defoliation and spectral data, and to b) identify the situations or conditions where contemporary remotely sensed imagery can be used in assessing crop loss due to hailstorm. The first objective focused on damage assessment on sorghum and corn crops in the Darling Downs region, while the second objective looked at the practicability of incorporating remotely sensed data in the operational crop loss adjustment.

REMOTE SENSING OF CROP DAMAGE FROM HAILSTORM

Remote sensing has been used in agriculture for many decades [see, for example, the review of Moran, et al., 1997]. In general, spectral data allows the discrimination of cropping from non-cropping areas, and to various degrees, the detection of health and vigour between and among crops. However, it is often difficult to generalise on what crop attributes can be exactly detected, as well as what to recommend as a “standard” approach in extracting crop information. Remote sensing is dictated by a number of complex, often interacting factors that pertain to energy source, sensor, atmospheric condition, energy/matter interactions at the earth surface, data handling and processing systems, and data users [Lillesand and Kiefer, 1987].

The plant’s stage of growth and the degree of damage (often assessed by quantifying defoliation) determine yield loss [Bullen, pers. comm.]. Defoliation affects the plants’ ability to effectively conduct photosynthesis because of the reduction in leaf area. Moreover, the amount of defoliation is also related to the plant’s ability to recover from hail-induced stress. Thus, defoliation is a key parameter being used by adjusters in crop loss assessment. Incidentally, physiological changes on crops associated with defoliation can alter the reflectance properties of plants and leaves. This can then make remote sensing a viable tool to quantify crop defoliation.

The usefulness of spectral data in detecting or quantifying leaf area or biomass is well documented [e.g. Wiegand, et al., 1991]. For instance, in a study of crop damage by frost in Greece, regression analysis showed that there was a statistically significant correlation ($r = -0.71$) between crop damage and average NDVI values [Silleos, et al., 2002]. In this study, the estimated percentage of damage as determined by the agriculturists and the NDVI models agree in 73% of the examined fields. In a separate study involving forest vegetation, it was demonstrated that defoliation severity in aspen can be detected with CASI image data [Moskal and Franklin, 2004].

Specific to crop damage assessment caused by hailstorm, there are few studies reported in the academic literature. On corn and soybean fields in Nebraska, multispectral and close-range hyperspectral data were used to evaluate the impact of artificially induced hail damage [Peters, et al, 2000]. In that project, a Landsat TM scene was also evaluated for its potential contribution in the evaluation of hail damage on crops. Their results showed that multispectral imagery is adequate for the detection of ground area and relative level of hail damage in corn and soybean crops.

More recently, hyperspectral and multispectral aerial imagery systems were used to assess stand loss and defoliation in maize [Erickson, et al., 2004]. They found that incremental differences in plant damage resulted in incremental differences in spectral responses. It was concluded that remote sensing could be used to improve the accuracy of estimating crop damage as long as adequate ground reference for different levels of crop damage exists.
While the above review is not exhaustive, there are indications that the use of remotely sensed data can be valuable to crop damage assessment. Our present study aspired to contribute to the scant body of knowledge of how remote sensing technology can be utilised to enhance crop loss adjustment in the insurance industry.

**RESEARCH METHODS**

**Study Area, Crop Attributes and Data Acquisition**

This project covered three separate study sites in the Darling Downs region, Queensland, Australia (Table 1 and Figure 1). The Toowoomba site has undergone a manually induced destruction on corn plots by cutting, bending, and shredding of leaves, to approximate defoliation at 100%, 75%, 50%, 25% and 0% levels. After 14 days of damage, reflectance data using the ASD FieldSpec® Handheld spectrometer [Analytical Spectral Devices, 2002], covering the visible to near-infrared range (325nm to 1075nm), were collected at the canopy level. Each sample was measured at a height that corresponded to a field of view of about 50 cm diameter.

<table>
<thead>
<tr>
<th>Study Area</th>
<th>Crop</th>
<th>Stage of Growth</th>
<th>Range of Defoliation</th>
<th>Spectral Data Acquired</th>
<th>Days Elapsed after Hailstorm/Damage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Postle St., Toowoomba</td>
<td>Corn</td>
<td>8-12 leaf stage</td>
<td>0 to 100%</td>
<td>Reflectance data from handheld ASD spectrometer (350-1075nm)</td>
<td>14 days</td>
</tr>
<tr>
<td>Dalby</td>
<td>Sorghum</td>
<td>soft dough</td>
<td>5 to 70%</td>
<td>Landsat 7 and SPOT 4</td>
<td>20 days for Landsat, 21 days for SPOT</td>
</tr>
<tr>
<td>Felton South</td>
<td>Sorghum</td>
<td>9-leaf</td>
<td>0 to 30%</td>
<td>Reflectance data from handheld ASD spectrometer (350-1075nm)</td>
<td>14 days</td>
</tr>
</tbody>
</table>

The second site, located in Dalby, covered sorghum fields that were damaged by a hail event on 1st February 2004. Landsat 7 imagery was purchased as an orthorectified image, while the SPOT 4 data was georectified using image-to-map registration to GDA94 road data. GPS data was calibrated to known survey points to within 2-metre accuracy of ground observation points taken by a field assessor.

The last study site was located in Felton South. On 2nd December 2004, a hail event occurred on the 28-day sorghum crop. Two weeks after the event, reflectance data using the same ASD spectrometer were collected at the canopy level. Each sample was measured at a height that corresponded to a field of view of about 50 cm diameter.

**Data Pre-processing**

For the ASD spectrometer data covering the Toowoomba and Felton South study sites, each file was exported into a spreadsheet format. Graphical plots of the spectra were examined to check for potential erroneous samples, as well as to initially explore the nature and magnitude of the differences between sample measurements. “Noisy” bands covering the spectral ranges 325-399nm and 901-1075nm were removed and thus excluded from the analysis.

Guided by GPS points, sample “pure pixels” corresponding to hail damage areas were delineated on both Landsat and SPOT imagery. Then, the DN values of damaged areas (2x2 pixels for Landsat and 3x3 pixels for SPOT) were separately extracted to calculate a mean value for each site. These average values were used for the correlation and regression analyses.
Figure 1. (a) corn with simulated hail damage at Postle Street, Toowoomba, (b) sorghum damaged by hailstorm in Dalby, (c) sorghum damaged by hailstorm in Felton South, and (d) Landsat 7 image of the Dalby site damaged by hailstorm.

Data Analysis

For all data sets, correlation analysis was done to determine the statistical associations between defoliation and spectral data. Then, to assess the predictive power of the relationship between variables, a Partial Least Squares (PLS) Regression using Unscrambler 9.1 [CAMO, 2004] software was implemented for each data set obtained from the three study sites.

PLS regression is a bilinear modelling method for relating the variations in one or several response variables (Y-variables) to the variations of several predictors (X-variables), with explanatory or predictive purposes [Esbensen, 2002]. Unlike the classical multiple regression technique, PLS performs particularly well when the various X-variables have high correlation (which is often the case for multispectral and hyperspectral data). Information in the original X-data is projected onto a small number of underlying (“latent”) variables called PLS components.

For PLS regression, all three datasets were analysed using the full cross-validation (leave-one-out) technique. The root mean error of prediction (RMSEP) was calculated, which gave the measurement of the average difference between predicted and measured response values. It can be interpreted as the average prediction error, expressed in the same unit as the original response value [CAMO, 2004].

Feasibility Analysis for Operational Implementation

A two-day workshop involving experts in the industry was conducted to identify the situations or conditions where contemporary remotely sensed imagery can be used in assessing crop loss due to hailstorm. A total of seven staff from Freemans Australia (experienced crop loss assessors and adjusters) and the University of Southern Queensland (remote sensing specialists and statistician) brainstormed on the merits and shortcomings of the current remote sensing technology for crop loss assessment. Aside from the experience and knowledge by the experts, the results of our spectral-defoliation study provided valuable information during the discussion.
A “feasibility matrix” of the assessment results was generated. It contains the following evaluation criteria and categories, rated on the scale “high feasibility”, “moderate feasibility”, and “low feasibility”:

- role/use - supportive, definitive
- crop stage - phase 1, phase 2, phase 3
- timing - 1-3 days, two weeks
- external factors - no to minimal effect, high influence
- damage extent - small area, widespread
- intensity of damage - low, moderate, high
- locality/ accessibility - less accessible, more accessible

RESULTS AND DISCUSSION

Defoliation and Spectral Data

The plots of reflectance data of corn and sorghum crops with various defoliation levels (Figure 2) indicate the incremental differences in spectral responses. This agreed with the theoretical expectations and some of the previous related studies (e.g. Erickson, et al., 2004). In general, the near infrared (NIR) region exhibited the greatest difference, where “no damage” canopy (0%) has significantly higher reflectance values than those damaged canopies (i.e. 10%, 30%, 50% and 100%). However, it should be emphasised that this was the general trend, acknowledging that there were few “inconsistencies” due to some confounding factors described later in this paper.

The results of correlation analyses indicated that defoliation and spectral data from Landsat and SPOT imagery are highly correlated (highest values are r = -.91 and r = -0.93, respectively) (Table 2). There relationships were expected, since previous research indicated that there is a high correlation between NIR reflectance and some measures of green vegetation amount (e.g. LAI and biomass). In the NIR region, reflectance is greatly influenced by plant cell structures. As hail destroys the structure of the leaves by stripping and tearing, it can result to reduction of the NIR reflectance.

However, for the hand-held spectrometer data, the correlations were variable over the two sites (i.e. highest values are r = .71 for the trial plots, and r = -.40 for the young sorghum crops.). The relatively low correlation for the young sorghum crops prompted us to identify potential confounding factors. They were recognised as:

- the crop stage of growth
- the effect of the background soil
- the timing of acquisition
- the equipment-operator factor
- the external factors that can cause within-field spatial variability (e.g. soil, micro-topography, pests and diseases, cropping history, etc.).
Table 2. Correlations between defoliation and spectral data.

<table>
<thead>
<tr>
<th>Study Area</th>
<th>Crop</th>
<th>Stage of Growth</th>
<th>No of Samples (n)</th>
<th>Highest Correlation Coefficient (r) Obtained</th>
</tr>
</thead>
<tbody>
<tr>
<td>Postle St., Toowoomba</td>
<td>Corn</td>
<td>8-12 leaf stage</td>
<td>22</td>
<td>0.71 (680nm)</td>
</tr>
<tr>
<td>Dalby</td>
<td>Sorghum</td>
<td>soft dough</td>
<td>7*</td>
<td>-0.91 (Landsat, band 4, NIR)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.93 (SPOT, band 3, NIR)</td>
</tr>
<tr>
<td>Felton South</td>
<td>Sorghum</td>
<td>9-leaf</td>
<td>62</td>
<td>-0.40 (900nm)</td>
</tr>
</tbody>
</table>

*The number of samples is very low due to crop damage availability and the need to group similar growth stage level. However, each sample is an average of 2x2 pixels for Landsat and 3x3 pixels for SPOT.

In the above case (i.e. sorghum crop in Felton South), the equipment-operator factor and the external factors were the most likely reasons for the unexpected results. First, the angle and height of the spectrometer over the canopy (which determined the “footprint” field of view) may not be consistently followed. A slight difference in the angle and height of the spectrometer could spell a significant difference in the reflectance of canopies. This is particularly true in this study site, since the crops were young (i.e. foliage projective cover is low) and the soil background can potentially confound the “consistency” of reflectance. This demanded the need to develop a platform or stand that will ensure the consistency of sensor angle and height during field data collection.

Lastly, within a paddock, it was noticed that certain parts of the study site have lower elevation than the rest of the field (i.e. micro-relief differences). With this, it is possible that the differences in spectral responses may not be entirely due to hail damage, but to other site factors that can cause within-field spatial variability. Therefore, such situation could make the estimation and prediction more difficult.

The results of PLS regression indicated that the spectral data are good predictors of defoliation (Tables 3 to 5 and Figure 3). The cross-validated prediction accuracy ranges from 80.90% (for the corn crops and ASD spectrometer) to 85.12% (sorghum crops and SPOT data). Given these good results, and in view of the low correlation of sorghum crops at Felton South previously calculated, it indicated that the PLS regression modelling was able to handle (and separate) the structured information from the data noise. Furthermore, PLS regression allows the systematic identification, evaluation, and removal of sample outliers, which resulted in better prediction accuracies.

Table 3. PLS Regression Results of Corn Defoliation (Artificial Hail Damage) and Hyperspectral Data (n=16)

<table>
<thead>
<tr>
<th>Data</th>
<th>Optimal no. of PLS factors</th>
<th>Calibration</th>
<th>Cross-Validation (leave-one-out)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>R*</td>
<td>RMSEC*** value</td>
<td>R*</td>
</tr>
<tr>
<td>1. Raw spectra</td>
<td>3</td>
<td>0.95</td>
<td>11.12</td>
</tr>
<tr>
<td>2. First derivative</td>
<td>3</td>
<td>0.93</td>
<td>11.38</td>
</tr>
</tbody>
</table>

*R – Correlation between predicted and measured values      ** RMSEC – root mean square error of calibration     *** RMSEP – root mean square error of prediction

Table 4. PLS Regression Results of Sorghum Defoliation and Hyperspectral Data (n=52)

<table>
<thead>
<tr>
<th>Data</th>
<th>Optimal no. of PLS factors</th>
<th>Calibration</th>
<th>Cross-Validation (leave-one-out)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>R*</td>
<td>RMSEC*** value</td>
<td>R*</td>
</tr>
<tr>
<td>DURING ASSESSMENT</td>
<td>8</td>
<td>0.92</td>
<td>3.72</td>
</tr>
<tr>
<td>2. First derivative</td>
<td>8</td>
<td>0.97</td>
<td>2.2</td>
</tr>
<tr>
<td>PROJECTED LOSS</td>
<td>1. Raw spectra</td>
<td>8</td>
<td>0.94</td>
</tr>
<tr>
<td>2. First derivative</td>
<td>7</td>
<td>0.96</td>
<td>5.68</td>
</tr>
</tbody>
</table>

*R – Correlation between predicted and measured values      ** RMSEC – root mean square error of calibration     *** RMSEP – root mean square error of prediction
Table 5. PLS Regression Results of Sorghum Defoliation and Landsat and SPOT Data (n=7)

<table>
<thead>
<tr>
<th>Data</th>
<th>Optimal no. of PLS factors</th>
<th>Calibration</th>
<th>Cross-Validation (leave-one-out)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>R*</td>
<td>RMSEC*** value</td>
</tr>
<tr>
<td>Landsat 7</td>
<td>1</td>
<td>0.93</td>
<td>7.21</td>
</tr>
<tr>
<td>SPOT</td>
<td>1</td>
<td>0.92</td>
<td>7.62</td>
</tr>
</tbody>
</table>

*R – Correlation between predicted and measured values  ** RMSEC – root mean square error of calibration  *** RMSEP – root mean square error of prediction

For the corn crop at Postle Street, Toowoomba, the regression coefficients with the most significant X-variables were the following: a) NIR region (highest at 730nm), b) reflectance red-edge region (highest at 720nm), c) red region (highest at 680nm), and d) green region (highest at 550nm) (Figure 3a). In the case of sorghum crop at Felton South, the green region (high values at 550nm, 523nm, and 590nm) dominated the coefficients that are highly significant (Figure 3b). Lastly, for the Dalby site involving sorghum crop, both Landsat and SPOT images had NIR as the highest regression coefficient, indicative of its importance in the regression model (Figures 3c and 3d). Overall, the results in this part agreed with our expectations: these are the regions and bands that are known to be relevant in sensing vegetation attributes.

![Regression Coefficients](image1)

![Regression Coefficients](image2)

![Regression Coefficients](image3)

![Regression Coefficients](image4)

Figure 3. Regression coefficients for (a) for corn defoliation, (b) sorghum defoliation, (c) sorghum defoliation and Landsat 7 data, and (d) sorghum defoliation and SPOT 4 data. The higher the value of a coefficient, the more significant it is in the prediction model.

Feasibility Analysis for Operational Implementation

The brainstorming sessions conducted during the workshop generated a 7x7 column-rows feasibility matrix (Figure 4). The experts agreed that remotely sensed imagery can be best used for crop assessment in the following situations:

- in a supportive (not “deterministic”) role;
- in phase 2 (i.e. six-leaf to flowering) crop stage;
- about three days after the hailstorm event;
- in fields with minimal effect from external factors;
- in areas where damage is widespread;
- in fields where damage is of high intensity; and
- in less accessible areas.

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Role/use</th>
<th>Crop Stage</th>
<th>Timing</th>
<th>External Factors</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Supportive</td>
<td>Definitive</td>
<td>Phase 1</td>
<td>Phase 2</td>
</tr>
<tr>
<td>Role/use</td>
<td></td>
<td></td>
<td>HF</td>
<td>HF</td>
</tr>
<tr>
<td>Definitive</td>
<td></td>
<td></td>
<td></td>
<td>Satellite - NF - Harvest</td>
</tr>
<tr>
<td>Crop Stage</td>
<td>Phase 1</td>
<td></td>
<td>HF</td>
<td>HF</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Satellite -</td>
<td></td>
<td>HF</td>
</tr>
<tr>
<td></td>
<td>Phase 2</td>
<td>Satellite -</td>
<td></td>
<td>HF</td>
</tr>
<tr>
<td></td>
<td>Satellite -</td>
<td>Flowering</td>
<td>HF</td>
<td>HF</td>
</tr>
<tr>
<td></td>
<td>Phase 3</td>
<td>Harvest</td>
<td>HF - Flowering</td>
<td>HF</td>
</tr>
<tr>
<td>External Factors</td>
<td>No to minimal effect</td>
<td>HF</td>
<td>HF</td>
<td>HF</td>
</tr>
<tr>
<td>Damage Extent</td>
<td>High Influence</td>
<td>HF</td>
<td>HF</td>
<td>HF</td>
</tr>
<tr>
<td>Intensity of Damage</td>
<td>Widespread</td>
<td>HF</td>
<td>MF</td>
<td>MF</td>
</tr>
<tr>
<td>Locality/Accessibility</td>
<td>Less accessible</td>
<td>HF</td>
<td>HF</td>
<td>HF</td>
</tr>
</tbody>
</table>

Figure 4. A feasibility matrix showing the seven criteria used and their assessments based on the scale “high feasibility” (HF), “moderate feasibility” (MF), and “low feasibility” (LF).

At the current level of technology, it was recognised that remote sensing can be used in a supportive role for crop loss assessment, rather than as the primary basis to determine crop damage. Despite the fact that regression methods can achieve good prediction accuracies, there are many confounding “external” factors that could make image-based estimation of crop damage less accurate for insurance purposes. Moreover, regression based models are empirical and “non-transferable”, thus will still require substantial ground reference information for a particular field. However, on the positive side, imagery can be used to get a “wider view” of the hail damage region, so that the deployment of resources and field assessors can be prioritised. Moreover, imagery can be also used as a cost-saving tool to rationalise field sampling procedures by indicating homogenous and heterogenous regions that govern sampling intensity.

Acquiring imagery by satellite sensors on the desired time is a potential limitation. It has been identified that the percentage defoliation is more accurate when estimated 7-10 days after the storm [Erickson, 2000]. However, this may not be achieved when cloud cover prevails over an area during the time of satellite passes. The use of airborne imagery can possibly solve this, but its cost could be prohibitive to capture relatively bigger areas.
In terms of maximising the cost-effectiveness of purchasing imagery, the damage areas over a region should be widespread and less accessible. If the damage is not widespread enough in terms of aerial extent or coverage (e.g. the damage is only about 100 sq.m. patch), then acquiring imagery is presumed to be uneconomical. Conversely, if the damage areas are relatively far from the assessors’ quarters (e.g. 8-10 hours drive), then remote sensing systems will be more valuable. Moreover, imagery will be more suited if the damage to the crops are of high intensity. If the damage is “light” or minor (e.g. defoliation is close to 0%), then the use of imagery is not warranted. Incremental differences of the spectral responses may not be detected by using imagery, especially those acquired by broadband sensors.

Lastly, the crop growth stage is a major factor in the accurate estimation of damage. When crops are damaged at the early stage of growth, it is possible that a remote sensor can detect crop damage, especially if the background soil reflectance is minimised. However, the issue arises when the plants started to physically recover until such time that the defoliation is virtually non-evident. When crops are assessed on this latter stage, spectral data is of little value.

CONCLUSIONS

Imagery and spectral datasets are good predictors of crop defoliation and can be used in crop loss assessment. Despite the potential, the presence and effects of several confounding factors can render predictive regression models less acceptable to the insurance industry. Consequently, remote sensing is acceptable for use in a supportive role for crop loss assessment. The imagery provides an acceptable synoptic view of the hail damage region, so that the deployment of resources and field assessors can be prioritised. They can be also used as a cost-saving tool to rationalise field sampling strategies and provide a check assessment. Future work should focus on how to restrict or isolate the effects of confounding factors during estimation to both improve the model and verify (or confirm) the usefulness and accuracies of this application.

ACKNOWLEDGEMENTS

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REFERENCES


CAMO (2004), The Unscrambler 9.1, Oslo: CAMO, Process AS.


