Spatial Yield Risk Across Region, Crop and Aggregation Method

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A researcher interested in crop yield risk analysis often has to contend with a lack of field- or farm-level data. While spatially aggregated yield data are often readily available from various agencies, aggregation distortions for farm-level analysis may exist. This paper addresses how much aggregation distortion might be expected and whether findings are robust across wheat, canola and flax grown in two central Canadian production regions, differing mainly by rainfall, frost-free growing days and soil type. Using Manitoba Crop Insurance Corporation data from 1980 to 1990, this research, regardless of crop or region analyzed, indicates that (i) spatial patterns in risk are absent; (ii) use of aggregate data overwhelmingly under-estimates field-level yield risk; and (iii) use of a relative risk measure compared to an absolute risk measure leads to slightly less aggregation distortion. Analysts interested in conducting farm-level analysis using aggregate data are offered a range of adjustment factors to adjust for potential bias.

Un chercheur qui s'intéresse à l'analyse du risque du rendement des cultures doit souvent composer avec un manque de micro-données provenant de l'exploitation. Bien qu'il soit possible d'obtenir des données sur les rendements spatialement cumulées auprès de divers organismes, ces données peuvent comporter des distorsions importantes dues à l'agrégation des données de base et être trompeuses si elles sont utilisées pour effectuer des analyses à l'échelle de l'exploitation. Le présent article traite de la quantité de distorsion due à l'agrégation à laquelle on doit s'attendre et examine si les résultats obtenus pour le blé, le canola et le lin dans deux principales régions productrices canadiennes, où les précipitations, les jours de croissance sans gel et le type de sol constituent les principales différences, sont robustes ou non. À l'aide des données obtenues auprès de la Société d'assurance-récolte du Manitoba pour la période 1980–1990, la présente étude, sans égard à la culture ou à la région analysée, indique (i) que les profils régionaux en matière de risque n'existent pas; (ii) que l'utilisation de données agrégées sous-estime considérablement le risque de rendement; (iii) que l'utilisation d'une mesure du risque relatif comparativement à une mesure du risque absolu entraîne légèrement moins de distorsion d'agrégation. Afin d'ajuster les données pour minimiser un biais éventuel, nous proposons une gamme de facteurs d'ajustement aux analystes intéressés à effectuer des analyses à l'échelle des exploitations à l'aide de données agrégées.

INTRODUCTION

Economists interested in capturing yield risk may choose from a range of data sources. For example, they can utilize experimental data from field research plots, GIS data collected from harvesting equipment or even publicly available data from various yield-reporting agencies. A trend in these aforementioned types of data is an ever-increasing level of spatial aggregation. Ideally, the research objectives would dictate the level of acceptable data aggregation. For example, if farm-level analysis is performed, then farm-level yield histories would be ideal. In reality, the data source often dictates the types of decisions (field level, farm level, county level etc.) that can be analyzed with the data. When farm-level data are not available, simulation data are often used for analyses (Taylor, Adams and Miller 1992; Foltz et al 1993) but are inappropriate for risk analysis due to their deterministic nature. Incomplete farm-level data, especially for risk analysis, is a common problem. The issue is exacerbated when an agricultural economist is added to a multidisciplinary project after the research design phase is completed (key data for economic analyses are often not collected) or when the experimental plot data are only marginally representative of farm-level conditions. Researchers are therefore often faced with a lack of representative farm-level yield data and thus choose, perhaps second best, spatially aggregated yield data for farm-level analyses.

Considerable research exists to test for the amount of distortion that is introduced when using aggregate data for farm-level decisions (Carter and Dean 1960; Eisgruber and Schuhman 1963; Debrah and Hall 1989; Marra and Schurle 1994; Bechtel and Young 1999; Rudstrom et al 2002; Wang and Zhang 2002). Some aggregation adjustments are therefore necessary to reflect differences between aggregate and farm-level data to avoid biased results (Fulton, King and Fackler 1988; Skees and Nutt in Mapp and Jeter 1988; Popp, Dalsted and Skold 1997).

It is the lack of an unbiased data adjustment process that has prompted this extension of the research provided by Rudstrom et al (2002) that examined differences in the level of variance aggregation distortion for hard red spring wheat[1] for several municipalities within a risk area in Manitoba. While aggregation bias, for the most part, appeared to favor underestimation of yield risk for wheat, questions about the robustness of these findings across crops and other production regions arose. Since wheat is considered a relatively low-risk crop in comparison to other crops like canola and flax (Popp and Rudstrom 2000), one objective of this paper is to provide further empirical evidence of the type of distortion that can be expected between quarter section yield data and data that have been aggregated to some degree for crops other than wheat. The second objective is to examine similarities or differences in aggregation bias across different production regions—i.e., do production regions with different soil types and weather patterns exhibit similar aggregation bias? The final objective is a comparison of spatial yield risk patterns obtained when using different clustering metrics.

BACKGROUND

The following paragraphs highlight (i) a definition of aggregation bias; (ii) the relevance of aggregation bias from the perspective of producers and crop insurance agents and (iii) differences in crops and production regions analyzed in this study.

With an ever-increasing emphasis on risk management in agriculture (Harwood et al 1999), analysts attempting to capture an individual decision maker's production and price risk may be introducing biased research results if aggregation distortions exist. Table 1 highlights the issue of yield risk bias that decision makers face when using temporal yield risk measures obtained from spatially aggregated yield data (right side of table 1) compared to an average of yield risk estimates from individual fields (bottom row of

Table 1. Hypothetical examples of data aggregation distortions in variance estimates

	Field yields in bu/acre[a]					
Year	1	2	3	4	Avg. yield (Fields 1 to 4)	Year
Scenario 1						
1	31	–	29	30	30.0	1
2	30	31	30	27	29.5	2
3	29	30	31	–	30.0	3
4	32	–	–	28	30.0	4
5	–	32	31	30	31.0	5
6	28	29	27	–	28.0	6
7	–	28	28	29	28.3	7
8	29	31	30	31	30.3	8
Field variance estimates (**FVE**)[b]	2.17	2.17	2.29	2.17	**1.00**	Agg. yield var. estimate (**AYV**)[c]
Mean yield	29.83	30.17	29.43	29.17	29.64	Agg. mean yield
FCV[b]	4.93%	4.88%	5.14%	5.05%	**3.38%**	Agg. CV (**ACV**)[c]
Avg. of FVE (**EYV**)[d]		**2.20**			*0.46*	AYV/EYV (R_1)[e]
Avg. of CV (**ECV**)		**5.00%**			*0.68*	ACV/ECV (R_2)
Scenario 2						
1	29	–	29	27	28.3	1
2	29	31	31	28	29.8	2
3	30	32	31	–	31.0	3
4	27	–	–	25	26.0	4
5	–	31	31	28	30.0	5
6	30	31	30	–	30.3	6
7	–	31	30	28	29.7	7
8	28	29	28	27	28.0	8
Field variance estimates (**FVE**)[b]	1.37	0.97	1.33	1.37	**2.58**	Agg. yield var. estimate (**AYV**)[c]
Mean yield	28.83	30.83	30.00	27.17	29.14	Agg. mean yield
FCV[b]	4.05%	3.19%	3.85%	4.30%	**5.52%**	Agg. CV (**ACV**)[c]
Avg. of FVE (**EYV**)[d]		**1.26**			*2.05*	AYV/EYV ($\mathbf{R}_1$)[e]
Avg. of CV (**ECV**)		**3.85%**			*1.43*	ACV/ECV ($\mathbf{R}_2$)

[a]Field yield time series may not have observations each year due to crop rotations and other considerations.

[b]Field variance estimates (FVE) are the temporal variance of yields for a particular field. Field coefficient of variation (FCV) is the FVE divided by the mean yield for the field.

[c]Aggregate yield variance (AYV) is the temporal variance of spatially averaged yields. Aggregate coefficient of variation (ACV) is the AYV divided by the mean yield of the spatially averaged yields.

[d]FVE and FCV are averaged across fields to arrive at EYV and ECV, respectively. These estimates of variance and coefficient of variation are considered unbiased for the average field.

[e]The ratios of the bold numbers in the table reflect the amount of aggregation distortion. R values of 1 would indicate no distortion, whereas numbers above/below 1 indicate under/over-estimation of yield risk when using aggregate risk measures. R values are reported in italics for both variance and coefficient of variation.

scenarios 1 and 2 in Table 1). Use of AYV (the temporal variance of spatially averaged yields or the variance of average yields) compared to EYV (average of field-level yield variance over time or the average of variances) can lead to over- or under-estimation of yield variance estimates using aggregate data as shown by the ratios of AYV/EYV (R_1) presented in Table 1. While EYV is the preferred aggregate risk measure, most researchers use AYV due to ease of data access. The scenarios point out that even if individual field risk is similar across an area, the aggregate measure can be either higher or lower.

Using Table 1 as a point of reference and replacing quarter-section wheat yield information from a municipality with the hypothetical four field observations in the table, the municipality AYV for wheat underestimated the EYV for quarter-section data for each of the nineteen municipalities analyzed (Rudstrom et al 2002). The implication for the single crop, wheat, was that municipality data were not appropriate for farm-level risk decisions because they consistently underestimated yield variability. Statistical clustering of the temporal variance of a quarter section's yield history (FVE) into groups of similar FVE was performed to determine if spatial patterns in yield risk existed and, therefore, a less spatially biased estimate of yield risk could be reported (i.e., dividing municipalities or larger areas into sub-regions of similar risk). Ordering these clusters or sub-regions of municipalities by magnitude of risk showed that (i) differences in R_1 values for each cluster were not related to the level of risk; and (ii) no distinctive spatial patterns in FVE measures were apparent. Quarter sections contained in a cluster were spatially dispersed throughout a municipality rather than geographically located in close proximity. While distortions at the municipality level of aggregation always had R_1 values less than 1 (scenario 1 in Table 1), at the smaller cluster level of aggregation (sub-regions of a municipality), R_1 values were sometimes greater than 1 (scenario 2 in Table 1). Aggregation bias for FVE thus appeared to favor underestimation of yield risk the greater the number of observations aggregated and/or the greater the range in FVE observed. How does this issue affect decision makers in agriculture?

Row crop production is an important component of agriculture in Manitoba. In 2001 there were 3.7 million acres of wheat, 436,000 acres of flax and 1.9 million acres of canola planted in the province (Statistics Canada 2001). In terms of farm participation, 44% of farms produced wheat, 30% produced canola and 13% of farms produced flax.

Crop producers use crop insurance to help manage their risk. Payout to producers is based on either a producer's long-term yield history or the risk area average yield if the producer does not have a yield history. Adjustments are made to individual producer premiums based on this long-term average yield relative to the risk area long-term average yield, or the individual producer index.

Data aggregation is done at the farm level when determinations of insurance payouts are made. In addition to average crop yield, farmers are also concerned with yield variability. Further, it is the temporal variance in farm-level yields that is likely the basis for making crop acreage allocation decisions. At the farm level, the questions become how does average annual yield on their fields vary and is the risk acceptable for the farm operation? Put another way, what is the farm-level EYV? The question related to data aggregation is how does the average of the temporal variation of fields (EYV) compare with the variance of average annual yields across fields (AYV)? Since the latter (AYV) is most often used in the absence of producer data, the question is whether an adjustment for this distortion across crops and space is needed.

Since growing conditions for crops vary across Manitoba, the province is divided into a number of risk areas. This study focuses on two risk areas, 4 and 12, in southwestern and southeastern Manitoba, respectively. Each risk area has relatively similar growing conditions and soil types. The Red River Valley Risk Area 12, located mostly to the south of Winnipeg, is a relatively low-risk production area of heavier Osborne clay soils. It generally receives adequate precipitation at 20 inches annually with 15 inches from April to September. The region averages 1,750–1,800 growing degree days[2] annually (The Manitoba Co-operator 2000). Plant moisture stress is the difference between the amount of water a crop can potentially use and the amount of water it actually gets from planting to maturity. In Risk Area 12, the moisture stress for wheat ranges from −0.2 to −0.4 inches. Other parts of the province have more challenging growing conditions. Risk Area 4 is located around the city of Brandon (approx. 120 miles west of Winnipeg) and compared to Risk Area 12, is characterized by sandier soils. The average growing degree days in this region are 1,600 to 1,650. The moisture stress index for wheat is −0.6 to −0.8 inches.

METHODOLOGY

Similar to the procedure described in Rudstrom et al (2002), it is possible to group or cluster quarter sections that have similar yield variation across time in order to be able to discern spatial patterns in yield risk across a production region. If spatial patterns are evident, clustering allows for (i) insights on the range of aggregation distortion to expect across different regions of aggregation and/or (ii) modifications to MCIC-defined risk areas considered to be similar in terms of yield risk.

Cluster analysis allows objects to be placed in groups, such that objects in the groups are similar. In this case, objects are quarter sections of land and the clustering statistics used to arrange the objects are the crop yield coefficient of variation (FCV; see Table 1) and the field variance estimate (FVE; see Table 1) as used by Rudstrom et al (2002). Since different crops are evaluated and since average yields vary across production regions, it is expected that variance alone is not appropriate for the comparison of risk within the crop across regions or across crops and regions. A relative risk measure (FCV) is chosen to cluster quarter sections.

A number of clustering procedures are available. The nonhierarchical method of k-means clustering is used here (Johnson and Wichern 1998). The quarter sections within a municipality are partitioned into an unknown number of k clusters of like clustering statistic (i.e., FVE and/or FCV) where k is the number of clusters specified in advance and can be changed. An initial set of k seed quarter sections are selected as starting points for the clusters with their FVE or FCV as seed values. Using these seeds, remaining quarter sections are assigned to a cluster nearest to one of the k seeds. After all the quarter sections are assigned to k clusters, cluster means (of FVE or FCV) are calculated to replace the initial seed values. Using these cluster means, quarter sections are reassigned based on minimum distance to the k^{th} cluster mean. The process continues until no more reassignments take place or the distance between cluster means and quarter sections assigned to different clusters is minimized. Since the technique is somewhat sensitive to the seeds used as starting points as well as the number of seeds to use, the value of the pseudo F-statistic for incremental values of $k = 2, \ldots, 10$ was maximized (Milligan and Cooper 1985).

Once the clustering was performed and clusters were ordered from the lowest to highest absolute and relative risk, aggregation distortion statistics ($R_1 = \text{AYV}/\text{EYV}$ and $R_2 = \text{ACV}/\text{ECV}$) were calculated similar to the procedure shown in Table 1 for each of the municipalities. The cluster R_1 (R_2) values within a municipality were calculated as the AYV (ACV) for the municipality divided by the EYV (ECV) of a cluster, respectively. This is a deviation from Rudstrom et al's (2002) work as municipality rather than cluster AYV (ACV) was used in this study. Using cluster AYV (ACV) allowed analysis of differences in R value by size of aggregation region in Rudstrom et al's work. In this study the resulting cluster R values provide a range of aggregation distortion for a municipality depending on the range of risk present across clusters (i.e., a decision maker interested in using municipality risk estimates to make field-level decisions would adjust the municipality risk using the highest (lowest) R value if he thought the field had a low (high) yield risk history). Overall, this process results in cardinal measures of R_1 and R_2 with measurable differences across clusters.

To address the third objective of examining differences in clustering across clustering metrics, the difference between cluster numbers (determined using FCV compared to FVE) was analyzed and spatial yield risk patterns (using the cluster information) were compared.

A comparison of cluster number assignments by quarter section is complex since both the number and size distribution of clusters may differ by clustering metric in each municipality. Since cluster numbers using either clustering statistic were assigned in an increasing order of magnitude (i.e., a low cluster number had the lowest risk observations whereas a high cluster number had the highest risk observations), the difference in cluster number assignment (ΔCN defined as the FCV cluster number less the FVE cluster number) for each quarter section now becomes ordinal. Averaging ΔCN across quarter sections in a municipality indicates whether cluster assignments are similar across the clustering metric. In this study, a positive (negative) average indicates that FCV assignments tend to be in higher (lower) risk clusters than FVE assignments. This information was also visually analyzed by plotting ΔCN using ESRI ArcGIS v 8.3. The average of ΔCN is also affected by differences in the number and size distribution of clusters generated using the FCV and FVE clustering metrics. In cases where the two clustering statistics lead to a different number of clusters in a municipality, clusters with fewest observations were combined into a single cluster to make the number of clusters the same across clustering statistic. For example, if there was one more cluster using the FVE compared to the FCV metric, then two FVE clusters with fewest observations (next to each other in ordinal rank) were combined into one. This was done to be able to plot spatial differences in ΔCN and to test a hypothesis of average $\Delta\text{CN} = 0$ or no difference in ordinal risk assessment with alternative clustering metrics.

DATA

Crop yield data from MCIC was obtained for 1980–1990 for Manitoba. Annual per acre yields for wheat, flax and canola were recorded for each field that was insured by MCIC. Municipalities 510 and 561 are entirely contained in Risk Area 12 and municipalities 621 and 971 are within Risk Area 4 boundaries. Wheat and canola were clustered for all four municipalities. Flax clustering was not performed for Risk Area 4 due to the insufficient number of quarter section observations for flax in municipalities 621 and 971.

Table 2. Summary statistics for aggregated and field level yield data (1980–1990)

Risk area	Municipality ID		Canola	Flax	Wheat
12	510	No. of obs.[a]	11/115	11/228	11/719
		Mean yield[b]	22.8	18.4	33.8
		AYV/EYV = R_1[c]	59.2/95.0 = **0.62**	45.8/71.5 = **0.64**	124.7/188.0 = **0.66**
		ACV/ECV = R_2[c]	34%/45% = **0.75**	37%/44% = **0.82**	33%/39% = **0.85**
	561	No. of obs.[a]	11/178	11/116	11/583
		Mean yield[b]	21.3	17.3	33.1
		AYV/EYV = R_1[c]	39.8/82.5 = **0.48**	43.7/61.4 = **0.71**	114.0/154.5 = **0.74**
		ACV/ECV = R_2[c]	30%/42% = **0.70**	38%/45% = **0.88**	32%/36% = **0.90**
4	621	No. of obs.[a]	11/50	Not analyzed	11/279
		Mean yield[b]	23.0		31.3
		AYV/EYV = R_1[c]	56.1/81.3 = **0.69**		53.0/107.2 = **0.49**
		ACV/ECV = R_2[c]	33%/38% = **0.87**		23%/32% = **0.72**
	971	No. of obs.[a]	11/85	Not analyzed	11/265
		Mean yield[b]	22.1		27.3
		AYV/EYV = R_1[c]	39.3/87.6 = **0.45**		67.9/130.3 = **0.52**
		ACV/ECV = R_2[c]	28%/43% = **0.67**		30%/41% = **0.71**

[a]Number of observations represents the number of years of aggregate data used for the first number and the number of field or quarter section observations in the municipality for the second number.
[b]Mean yields are the same whether aggregate or by individual field/quarter section.
[c]Variance, coefficient of variation and R values are calculated as shown in Table 1.

Long-run averages of acreage allocated to wheat, flax and canola are approximately 40%, 16% and 20%, respectively. In order to eliminate quarter sections where the crop is not typically grown, quarter sections with too low a frequency of production were eliminated. For wheat and flax this meant using quarter sections where the crop was grown for at least 4 of the 11 years and for canola this meant using quarter sections where the crop was grown for at least 3 of the 11 years. These restrictions fit with typical crop rotations in the area and remove yield risk bias that may be introduced if yield observations were included where the crop is typically not grown.

While a quarter section is an area of 160 acres, fields could be less than 160 acres. It was possible to have, for example, two 80-acre fields on a quarter section. When there were multiple fields of a single crop on a quarter section in any given year, the simple average of the fields was calculated and reported for those quarter sections.

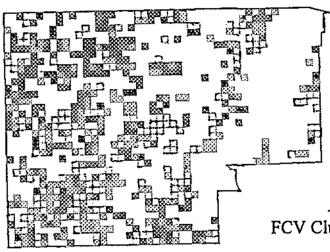
Using the annual field-level harvested yield, the average annual yield in the municipality or cluster was calculated for each of the three crops. The statistics were calculated for both an entire municipality as well as individual clusters within the municipality. Table 2 presents aggregate and average field statistics for the municipalities analyzed. Average yield for canola was one bushel less in Risk Area 12 municipalities than in Risk Area 4 municipalities. Since canola is a cool season crop, the slightly cooler Risk Area 4 (fewer growing degree days) may provide a better environment for this crop. Wheat, by

Cluster Information

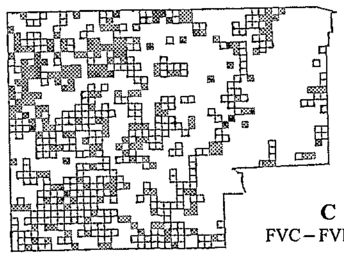
	FCV clusters			*FVE clusters*		
Mean ECV	Range of FCV	# of Obs.	Mean EYV	Range of FVE	# of Obs.
0.16	0.059 – 0.245	145	62.2	4.6 – 116.7	241
0.33	0.247 – 0.393	192	168.2	117.5 – 226.2	219
0.46	0.396 – 0.541	185	280.6	226.9 – 374.1	105
0.62	0.547 – 0.865	61	488.3	403.0 – 651.0	18

Cluster Difference Information

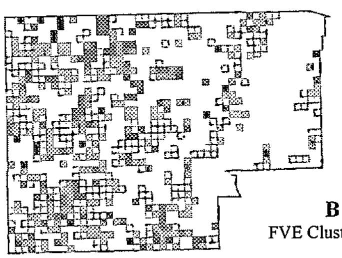
FCV cluster # - FVE cluster #	# of Obs.
-1	8
0	340
1	206
2	25
3	4



A
FCV Cluster Map



C
FVC – FVE Map



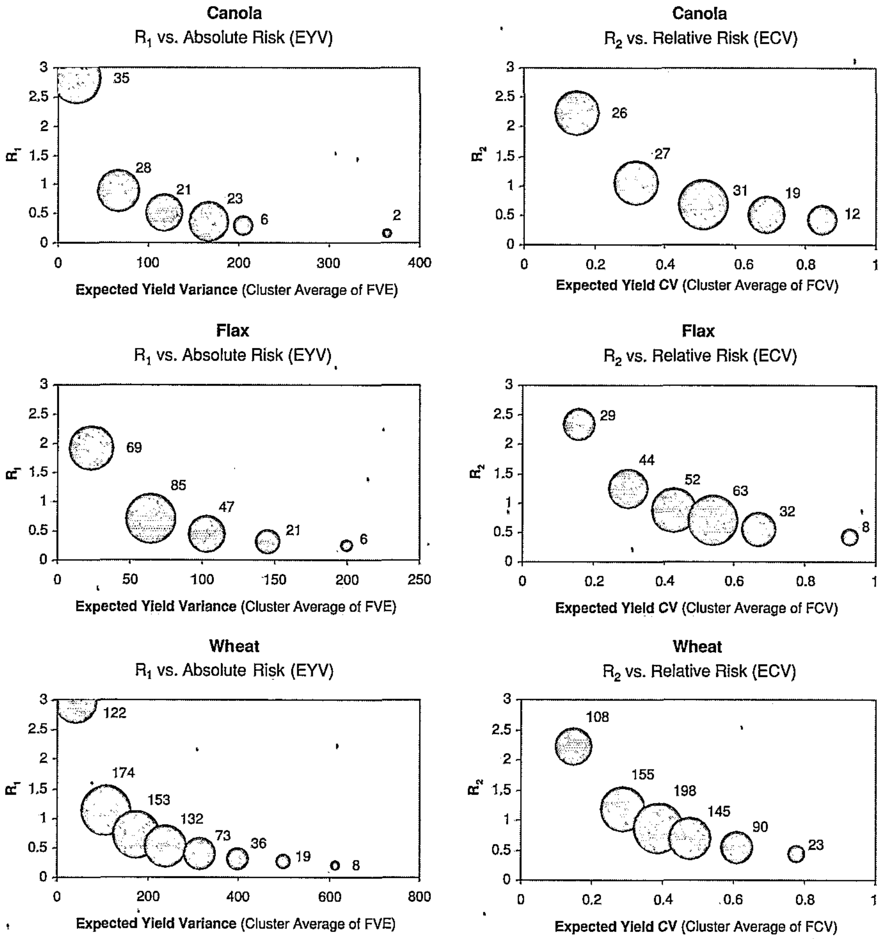
B
FVE Cluster Map

Figure 1. Comparison of spatial risk patterns using FCV vs. FVE statistics for clustering wheat in municipality 561

contrast, exhibited higher yields in Risk Area 12 than 4. In terms of aggregate relative risk (ACV), flax was more risky than canola or wheat in Risk Area 12. For each crop, the AYV statistics are less than EYV statistics as indicated by $R_1 < 1$ for each crop in each municipality. This indicates again that yield risk is underestimated using aggregate data. Using the ECV statistics in comparison to the ACV statistics, R_2, the relative risk is also underestimated, but the degree of underestimation is less than when R_1 is used. Therefore, analyses using CV would be less distorted than analyses using variance.

RESULTS

Using nonclustered aggregate data for all three crops in both risk areas tended to underestimate risk (note R_1, $R_2 < 1$ in Table 2). While both metrics revealed that use of aggregate risk measures underestimated risk, use of the relative risk metric for clustering R_2, exhibited less bias than the absolute measure, R_1. The absence of distinct spatial patterns in risk for wheat was repeated for canola and flax regardless of the production region or clustering metric in our study region. An example is shown in Figure 1 for wheat in municipality 561 in panels A and B. Both panels show clusters disbursed throughout the municipality with no recognizable, distinctive pattern. Similar observations (not shown



Notes: Bubbles represent clusters. The size of the bubbles reflects the number of quarter section observations per cluster as indicated by the data labels. See description of calculations for EYV, ECV, R_1 and R_2 in Table 3.

Figure 2. Comparison of R_1 and R_2 values against absolute and relative risk for canola, flax and wheat in municipality 510

here) were also found in other crops and municipalities and production regions. Aggregation bias thus existed to a similar extent across crops when analyzing R_1 and R_2 values. Obvious spatial risk patterns also did not exist in any of the crops mapped in this study.

There were differences in the number and size of clusters,[3] however, and the range in R_1 and R_2 values across all clusters showed variation among crops and municipalities. Figure 2 presents an example of these differences for municipality 510.[4] The bubbles are clusters with the size of the bubble determined by the number of quarter sections assigned to the cluster mean. The graphs, organized by crop (canola, flax, and wheat from top to bottom) and clustering metric (absolute risk (FVE) on the left vs. relative risk (FCV) on the right), also point out the distribution of clusters across both the levels of risk observed

Table 3. Minimum and maximum aggregation distortion ratios across clusters for absolute and relative risk measures by crop and risk area

			R_1[a]		R_2[a]	
Risk area	Municipality	Crop	Min.	Max.	Min.	Max.
12	510	Canola	0.16	2.80	0.40	2.22
		Flax	0.23	1.91	0.40	2.34
		Wheat	0.20	2.96	0.43	2.21
	561	Canola	0.12	1.19	0.48	1.06
		Flax	0.24	1.77	0.35	2.91
		Wheat	0.23	1.83	0.52	2.00
4	621	Canola	0.28	1.66	0.52	2.15
		Wheat	0.09	1.01	0.35	1.50
	971	Canola	0.11	2.00	0.40	1.14
		Wheat	0.15	2.07	0.32	1.30

[a] R_1 and R_2 are the municipality AYV and ACV divided by cluster EYV and ECV, respectively (i.e. Min. R_1 is the municipality AYV/EYV$_{\text{Cluster with Min. R}}$). A value of 1 represents no aggregation distortion bias. Dividing aggregate risk measures by the appropriate R value results in an estimate of field-level risk.

(horizontal axes) and the amount of aggregation distortion (R_1 and R_2 on the vertical axes). The size distribution of clusters was more even using R_2 compared to R_1. This suggests that yield and yield variance were positively correlated (i.e., high (low) quarter section mean yields with high (low) FVE reduced the range in FCV values compared to FVE in a production region). High FVE outliers were typically few in number and skewed the cluster distribution resulting in a tendency to have more clusters of different size using FVE compared to FCV. Table 3 summarizes minimum and maximum cluster R values. The lower limits in the range of R_1 and R_2 values were smaller when using the relative risk measure R_2 compared to the absolute risk measure R_1. Thus, a producer facing high yield variance on his operation (which happens relatively infrequently) would underestimate risk using an aggregate variance estimate more so than if he had used aggregate coefficient of variation. Both of these results suggest that use of a relative risk measure may show less aggregation distortion.

Table 3 highlights minimum and maximum distortion aggregation ratios (by how much do you have to divide an aggregate risk measure to arrive at field-level risk). While Table 2 showed that, on average, aggregate risk underestimates field risk regardless of crop and production region, the minimum and maximum R values show quite a range in distortion. Wheat yield variance at the field level, for example, could be as much as 2.96 times less than aggregate variance in municipality 510 (R_1 Max column in Table 3). By the same token, wheat yield variance at the field level may be as much as 11 times higher than aggregate variance in municipality 971 (inverse of R_1 Min column in Table 3). Differences in the range of R values across crops showed no distinct pattern in this study. These observations are in line with Rudstrom et al's (2002) findings (once adjusted for differences in cluster R value calculation as noted in the methodology section above) and lend (at least) partial support to the idea that aggregation distortions in risk are fairly similar across crops.

The second question related to the robustness of aggregation bias across production regions. Only wheat and canola were analyzed across regions, as the number of observations for flax was insufficient. Similar results were observed across production regions (Risk Areas 4 and 12) in terms of the tendency of aggregate data to underestimate yield risk (R values < 1 in Table 2). For both canola and wheat, the range of R values is slightly larger for Risk Area 12 compared to Risk Area 4 (Table 3). Overall, there did not appear to be other differences across production regions. This further suggests that Rudstrom et al's findings may be relatively robust across production regions where similar production practices are used and similar crops are grown.

The third question related to differences between using the relative risk measure rather than an absolute risk measure for clustering. In addition to clustering metric differences in number and size distribution of clusters as well as range in R values discussed above, panel C of Figure 1 shows that the spatial distribution of ΔCN showed no pattern. Table 4 presents average ΔCN and t-statistics to show tendencies in cluster number assignments using the two clustering metrics. On average FCV cluster numbers are higher, which is in line with the observation that yields and FVE are positively correlated.

CONCLUSIONS

Aggregation bias for wheat led to questions about the robustness of Rudstrom et al's (2002) results. Specifically, these questions were: (i) do crops other than wheat exhibit similar aggregation bias? (ii) is the aggregation bias similar across production regions characterized by different resource conditions? and (iii) does clustering by relative risk result in different spatial patterns and aggregation bias when compared to absolute risk?

Findings in this study lend robustness to the observations reported by Rudstrom et al (2002) in the sense that earlier findings on lack of spatial risk patterns and presence of aggregation distortion were broadened to other crops and another production region. The results suggest that risk is underestimated using aggregated data in most situations. Furthermore, aggregation distortions observed using absolute risk or FVE for the clustering statistic are greater than those observed for using relative risk or FCV. Thus analysts using aggregate coefficient of variation measures are introducing less bias to farm-level decisions than would be observed when using aggregated variance measures.

The lack of spatial patterns of yield variability, either absolute or relative, for wheat, canola and flax is an important finding in this study. It has implications for producers' cropping decisions and insurance decisions. First, producers often use aggregate yield data when deciding what crop to grow. Mean yield and temporal risk measures may not be applicable to their particular field. Understanding the potential magnitude of over- or underestimation can help producers in crop choice decisions. Second, and perhaps more importantly, the degree of aggregation bias has implications for larger farming operations. Since there do not appear to be spatial patterns in yield risk, farms with more than one quarter section may have a range of field risk observations across their entire farm. This raises the question of insuring field yields rather than farm yields when the farm consists of more than one quarter section.

Table 4. Comparison of clustering using FVE vs. FCV for wheat, canola and flax for risk areas 12 and 4

Municipality ID		Risk area 12		Risk area 4	
Crop	Item[a]	510	561	621	971
Canola	Average	0.200	−0.051	0.680	
	SD.	0.829	0.415	0.621	[b]
	No. of obs.	115	178	50	
	T-statistic	2.59[c]	−1.64	7.74 [c]	
Flax	Average	1.013			
	SD	0.847	[b]	Not analyzed	
	No. of obs.	228			
	T-statistic	18.05[c]			
Wheat	Average	−0.032	0.446	1.036	−0.589
	SD	0.858	0.634	0.724	1.329
	No. of obs.	719	583	279	265
	T-statistic	−1.00	16.98[c]	23.90[c]	−7.21[c]

[a]The average and standard deviation of the difference between cluster numbers was determined for each municipality by subtracting a quarter section's FVE cluster number from the FCV cluster number. Note that cluster numbers using either clustering statistic were assigned in an increasing order of magnitude (i.e. a low cluster number had lowest risk observations whereas a high cluster number had highest risk observations). In all cases except for municipality 561 for wheat, the two clustering statistics lead to a different number of clusters in a municipality. For these cases, the clusters with fewest observations were combined into a single cluster to make the number of clusters the same across clustering statistic. For example, in municipality 510 for canola, this meant combining FVE clusters 5 and 6 into one cluster so that the number of FVE and FCV clusters was the same and the average of the difference in cluster numbers could be calculated.
[b]For 971 Canola and 561 Flax, the difference in the number of clusters using FVE vs. FCV was deemed too large to combine clusters and arrive at a relatively unbiased difference statistic.
[c]The differences in FVE − FCV cluster numbers are statistically significantly different from 0 at $\alpha = 0.10$.

More rigorous statistical testing of comparisons across other crops, other production regions or even across metric used for clustering would be preferred to make stronger conclusions but is left for further study. Decision makers using aggregate data should thus likely continue to entertain sensitivity analysis for their chosen risk measure if they wish to extend their results to farm-level decisions. To arrive at farm-level risk, the use of distortion adjustment factors (R_1 or R_2) is suggested in this study as field-level risk may range from being nearly one third to as much as eleven times the aggregate statistics (Table 3).

NOTES

[1]Wheat will be used from this point forward to imply hard red spring wheat.
[2]Growing degree days is a heat measure useful for the growth and development of plants. It is calculated by subtracting the minimum temperature for plant development from the daily mean temperature and summing that daily difference over the period of analysis.

[3]*K*-means clustering was done using the FASTCLUS procedure in SAS Version 8 (SAS, Institute Inc., Cary NC) with the distance criterion being least squares and the maximum iterations being 15.

[4]More detailed results by crop, cluster and municipality are available from the authors upon request.

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