Life in the slow drain: Landscape structure affects farm ditch water quality

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HIGHLIGHTS
• Ditch pesticide levels decrease as forest increases in the surrounding landscape.
• Ditch nitrogen levels increase with increasing amounts of high-intensity crop cover.
• Increasing surrounding crop cover indirectly reduces aquatic invertebrate richness.
• Aquatic invertebrate richness is positively related to configurational heterogeneity.
• Management to improve farmland water quality should focus on landscape composition.

GRAPHICAL ABSTRACT

ABSTRACT
Agrichemical contamination is a major threat to aquatic ecosystems in farmland. There is a need to better understand the influence of the surrounding landscape on farm wetlands to recommend land management options that minimize water quality impacts from agricultural practices. We tested hypothesized relationships between landscape structure and multiple water quality measures in farm drainage ditches in a multi-landscape study in Eastern Ontario, Canada. We measured physicochemical water quality (levels of atrazine, glyphosate, neonicotinoid insecticides, inorganic nitrogen, and dissolved oxygen), and biological water quality indicators (aquatic macroinvertebrate richness, leaf litter decomposition, and Ceriodaphnia dubia population responses) in 27 farm ditches, and measured the amounts of forest cover and high-intensity crop cover (landscape composition), and field edge cover (landscape configuration) in 1-km radius landscapes surrounding each ditch sampling site. We used confirmatory path analysis to simultaneously model the direct and indirect relationships between the landscape predictors and water quality variables. Landscape composition measures were the strongest predictors of water quality: pesticides decreased as surrounding forest cover increased, and nitrogen increased with increasing amounts of high-intensity crop cover. Crop cover was also indirectly negatively related to macroinvertebrate richness via its effects on nitrogen and dissolved oxygen. We found no effects of landscape configuration on agrichemical levels, but there was some support for a positive relationship between macroinvertebrate richness and field edge cover. Our results indicate that aquatic macroinvertebrate richness is strongly impacted by fertilizer use in our region, and that macroinvertebrate richness is a more sensitive biotic indicator of farmland water quality than leaf litter decomposition or C. dubia responses. We conclude that, in our region,
1. Introduction

Agriculture is associated with many leading threats to fresh water systems and aquatic biodiversity (Allan and Castillo, 2007; Potter et al., 2004). Land conversion for farmland has resulted in extensive aquatic habitat loss and modification (Blann et al., 2009; DUC, 2010). Conventional farming practices impact surface water quality by promoting sedimentation, nutrient enrichment, and agrochemical contamination (Allan and Castillo, 2007). Impairments to water quality impact biological communities by altering physicochemical characteristics of habitats, such as dissolved oxygen levels, and inducing toxic effects on biota (Camargo and Alonso, 2006).

The water quality of remaining farmland water bodies is influenced by the amounts of different surrounding land cover types (Johnson et al., 1997). In general, water quality is negatively correlated with agricultural land cover and positively related to more natural cover, such as forest (Declerck et al., 2006; Gonzales-Inca et al., 2015; Li et al., 2015; Liu et al., 2012). Crop cover in the surrounding landscape negatively affects water quality through its role as a source of agrochemicals (Allan and Castillo, 2007). In contrast, forest cover is often positively associated with water quality not only because it limits the total amount of agrichemical-source cover within a landscape, but also because forest vegetation can reduce agrochemical loads in runoff through chemical uptake and transformation (Burken and Schnoor, 1998; Näsholm et al., 1998).

The water quality of farmland water bodies might also be influenced by the spatial arrangement of cover types in the surrounding landscape, i.e. landscape configuration. Increasing the complexity of the landscape pattern (‘configurational heterogeneity’) increases the amount of edge (Fig. 1). Positive relationships have been found between total edge density in catchments and the water quality of rivers (Uuemaa et al., 2005, 2007) and lakes (Liu et al., 2012). Uuemaa et al. (2007) speculate that more complex landscape patterns retain more nutrients in runoff, thus reducing inputs to water bodies. We therefore expect agrochemical levels in farmland water bodies to decrease with increasing landscape configurational heterogeneity.

In addition to chemical measures of water quality, aquatic organisms are also frequently used as water quality indicators (Baldy et al., 2007; Eagleson et al., 1990). Biotic water quality indicators could be indirectly related to landscape structure through the effects of landscape composition and configuration on water chemistry. Some indicators could also be directly influenced by landscape composition and configuration. For example, forest cover can provide habitat and facilitate the dispersal of some adult aquatic insects (Didham et al., 2012; Jonsen and Taylor, 2000) and vegetated field edges can provide refuge habitat and serve as movement corridors between forest patches for some adult aquatic invertebrates (Burel et al., 2004; Nasci, 1982).

Understanding the effects of landscape structure on farmland water quality can inform landowners and policy makers of effective options to minimize agrochemical inputs to surface waters and support biodiversity. Options involving changes to landscape configuration (rather than composition) would be particularly appealing because such options would not require taking land out of production. For example, increasing configurational heterogeneity by reducing mean crop field sizes has been suggested as an alternate conservation action to land retirement that can benefit biodiversity in agricultural landscapes (Collins and Fahrig, 2017; Fahrig et al., 2015; Monck-Whipp et al., 2018).

The goal of this study was to test hypothesized direct and indirect relationships between agricultural landscape structure (composition and configuration) and different measures of water quality in farmland drainage ditches, a common aquatic habitat in our study region. The predictions are shown in Fig. 2. We tested these predictions in a multi-landscape study in Eastern Ontario, Canada, across an area of approximately 5000 km² in the St. Lawrence watershed of the Mixedwood Plains ecozone. We measured physicochemical water quality (levels of atrazine, glyphosate, neonicotinoid insecticides, inorganic nitrogen, and dissolved oxygen), and biological water quality indicators (aquatic macroinvertebrate richness, leaf litter decomposition, and daphnia (Ceriodaphnia dubia) population responses) in farm drainage ditches, and measured the amounts of forest cover and high-intensity crop cover (landscape composition), and field edge cover (landscape configuration) in landscapes surrounding each ditch sampling site.

2. Materials and methods

2.1. Study sites

We selected 27 1-km radius agricultural landscapes, each centered on the middle of a 10-m survey transect in a farm drainage ditch, within Eastern Ontario, Canada. Approximately 47% of the study area is farmed, characterized by row crops (primarily corn, soybean, forages, and cereal grains), and pasture lands (EOWC, 2007; Mailvaganam, 2017).
Interspersed with farmland are patches of forest (~31%), wetlands and open water (~7%), and some urban cover (~5%) (OMAFRA, 2010). The farmed portion of the region was once dominated by wetlands and wet forests, and has a flat topography and many areas of low-permeability soils (City of Ottawa, 2011; DUC, 2010). The advent of post-European settlement farming in the late 18th century necessitated extensive land drainage, resulting in a loss of approximately 70% of pre-European settlement wetlands (City of Ottawa, 2011; DUC, 2010). Networks of open-system constructed drains (drainage ditches) have been established in our region for at least 150 years (Irwin, 1989) and are now ubiquitous features across the region. Closed-system, subsurface drains (i.e. tile drains) are also widespread across our study region. Tile drains remove water from upper soil layers, thus lowering the water table and facilitating crop root growth (Blann et al., 2009; City of Ottawa, 2011). At least 40% of fields are tile-drained in our study region (EOWC, 2007; OMAFRA, 2016). While generally regarded as hydrologic infrastructures of agriculture, drainage ditches are also wetland habitats that support aquatic biota (Verdonschot et al., 2011) and provide important ecosystem services in farmland, such as flood and erosion control (Levavasseur et al., 2012), groundwater recharge (Dages et al., 2009), and water purification (Moore et al., 2001). The 27 drainage ditches selected for this study are typical of the farmland ditches across the region (see Fig. 3 for example ditch sites). Conversations with landowners involved in our study revealed that the ditches are decades old, with age estimates ranging from 25 to 80 years. Some landowners were unable to estimate the ages of their ditches, indicating that they are likely older than 80 years. We recorded ditch physical characteristics at three points (0, 5, and 10 m) along each ditch transect in June. Average June water depths ranged from 5 to 54 cm (mean 22 ± 11 SD). Average channel width ranged from 0.88 to 6.27 m (mean 1.9 ± 1157

Fig. 2. Predicted relationships between three landscape predictors (proportion of the landscape in forest, high-intensity crop, and field edge), physicochemical water quality variables (mean dissolved oxygen (mg/L), a linear combination of mean atrazine, mean glyphosate and summed mean clothianidin, imidacloprid, and thiamethoxam, and a linear combination of total ammonia and nitrate-nitrogen + nitrite-nitrogen), and biological water quality variables (aquatic macroinvertebrate family richness, leaf litter decomposition, and Ceriodaphnia dubia survival and reproduction in collected ditch water). Predicted relationships are represented as arrows originating from predictors and pointing to responses, and the predicted direction of effect is shown as + or –.

Fig. 3. Examples of two of the 27 sampled farmland drainage ditches in agricultural landscapes of Eastern Ontario, Canada. Drainage ditches were sampled for water quality measures and these were related to surrounding landscape variables.
We analyzed relationships between ditch water quality measures and landscape structure within 1 km of the sampling site in each ditch. We defined landscapes as circular areas around sampling sites rather than ditch catchment areas because delineation of individual ditch catchments was not possible due to a lack of high resolution ground elevation data and the very flat nature of the region. We chose 1-km radius as the landscape size because previous work showed that high-intensity farming within this distance can influence the water quality of aquatic habitats (Koumaris and Fahrig, 2016), and because it encompasses the average dispersal and movement distances of many aquatic invertebrate terrestrial life stages (Conrad et al., 1999; Kovats et al., 1996).

Our ditch sites were located within a set of agricultural landscapes that were selected for a study investigating relationships between biodiversity and farmland heterogeneity, as measured by crop diversity and mean field size (Fahrig et al., 2015; Pasher et al., 2013). Landscape selection for this larger study aimed to sample spatially independent landscapes that represented the widest possible ranges in landscape predictors while minimizing the cross-landscape correlation between them (Fahrig et al., 2011; Pasher et al., 2013). Landscapes that met these criteria were identified by Pasher et al. (2013) based on land cover maps (30 m pixels) created from Landsat-5 satellite images from 2007. Once the preliminary sample landscapes (3 km × 3 km) were selected, accurate maps were created in 2011 and 2012 using air photography (40-cm resolution) and ground surveys (Fahrig et al., 2015). We assumed there were no significant changes in the landscapes between 2011–12 and 2014. We selected a subset (n = 27) of these landscapes that represented gradients in agricultural intensity (measured as the amount of crop cover) and the amount of field edge cover and contained a drainage ditch. We also attempted to control for the proportion of road cover and water cover within landscapes. We established a 10-m sampling transect in the widest accessible section of each ditch, and adjusted the landscape boundaries to the circular areas (1 km radius) around the point in the center of each transect. The proportion of road cover in the final 27 landscapes ranged from 0.004 to 0.025 (mean 0.01 ± 0.005 SD) and open water/wetland cover ranged from 0 to 0.07 (mean 0.01 ± 0.02 SD).

### 2.2. Landscape predictors

Our three landscape predictors were the proportion of the landscape in forest cover (square-root transformed), the proportion of the landscape in high-intensity agricultural cover (arcsine transformed), and the proportion of the landscape in edge cover, all in 1-km radius landscapes surrounding each ditch sampling site. High-intensity crop cover was the summed proportions of the landscape in the major crop types associated with high agrichemical inputs: corn, soy, and cereals (McGee et al., 2010). Edge cover was the proportion of the landscape covered in field edges. Field edges in our study region are areas of unplanted land between adjacent crops, and are comprised of remnant, semi-natural strips of vegetation including varying proportions of grasses, forbs, shrubs, and trees. Our edge cover variable included all types of field edges, as we were unable to determine the composition of all edges in the landscapes due to access limitations during ground surveys. We considered the proportions of forest cover and high-intensity crop cover as measures of landscape composition. We considered edge cover as a measure of landscape configuration because the amount of field edge in a landscape is related to the spatial arrangement of agricultural cover via a negative relationship with mean field size (Fig. 1). We standardized each of the three landscape predictors to a mean of 0 and SD of 1 prior to analysis. Predictor variable ranges, means, and standard deviations are shown in Table 1, and pairwise correlations are shown in Appendix A, Table A1.

### 2.3. Water quality response variables

#### 2.3.1. Agrichemicals

We collected water samples twice from each 10 m ditch transect during two collection periods from 6 to 13 June and 7 to 15 July 2014 for pesticide analysis, and once during the second collection period in July for inorganic nitrogen analysis. Agrichemical levels in surface waters are highest this time of year from runoff inputs following planting and post-planting applications and from seed treatments (Hladik et al., 2014; Thurman et al., 1992). The first sampling period began following an extended period of rainfall (four days) to maximize detection of agrichemical pluses from post-planting runoff. Grab samples were collected from the center of each ditch transect and kept in coolers until returned to the laboratory. At each sampling site during both collection periods we measured dissolved oxygen (DO) using a Horiba Scientific LAQUAact DO Meter OM-71, and we recorded pH and temperature using a Horiba Scientific LAQUAact pH meter.

Water samples were analyzed for pesticides at the National Wildlife Research Centre (NWRC) in Ottawa, Ontario, Canada, where high-performance liquid chromatography and tandem mass spectrometry were used to determine concentrations of atrazine, glyphosate, clothianidin, imidacloprid, thiamethoxam, and acetamiprid. Samples for atrazine and neonicotinoid analyses were held in 500 mL amber glass bottles and stored at 4 °C, and samples for glyphosate analysis were held in 500 mL plastic bottles and stored at −40 °C until analysis. The concentrations of the two herbicides were determined by methods developed by Laboratory Services at the National Wildlife Research Centre and the method used for neonicotinoid detection was adapted from Xie et al. (2011). Samples for all pesticide analyses were concentrated in a 1-km radius as the landscape size because previous work showed that high-intensity farming within this distance can influence the water quality of aquatic habitats (Koumaris and Fahrig, 2016), and because it encompasses the average dispersal and movement distances of many aquatic invertebrate terrestrial life stages (Conrad et al., 1999; Kovats et al., 1996).

### Table 1

Ranges, means, and standard deviations of variables used in the path model of the predicted relationships between drainage ditch water quality responses and landscape predictors (Fig. 2), and the number of ditch sites in which agrichemicals were detected. Pesticides, dissolved oxygen, and aquatic macroinvertebrate richness variables were measured twice from each of 27 ditches. Inorganic nitrogen and daphnia (C. dubia) survival and reproduction variables were measured once in water from the 27 ditches, and leaf litter decomposition rate was measured once in 25 ditches. Land cover variables were measured in 1-km radius landscapes surrounding each ditch sampling site. “LOD” = limit of detection.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Range</th>
<th>Mean</th>
<th>SD</th>
<th>No. sites</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Physicochemical water quality responses</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pesticides</td>
<td></td>
<td></td>
<td></td>
<td>27</td>
</tr>
<tr>
<td>Atrazine (μg/L)</td>
<td>0.005–2.76</td>
<td>0.17</td>
<td>0.44</td>
<td>27</td>
</tr>
<tr>
<td>Glyphosate (μg/L)</td>
<td>&lt;LOD–6.18</td>
<td>0.38</td>
<td>1.05</td>
<td>19</td>
</tr>
<tr>
<td>Total neonicotinoids (μg/L)</td>
<td>&lt;LOD–0.61</td>
<td>0.04</td>
<td>0.09</td>
<td>26</td>
</tr>
<tr>
<td>Clothianidin (μg/L)</td>
<td>&lt;LOD–0.42</td>
<td>0.02</td>
<td>0.06</td>
<td>26</td>
</tr>
<tr>
<td>Imidacloprid (μg/L)</td>
<td>&lt;LOD–0.01</td>
<td>0.001</td>
<td>0.002</td>
<td>17</td>
</tr>
<tr>
<td>Thiamethoxam (μg/L)</td>
<td>&lt;LOD–0.23</td>
<td>0.02</td>
<td>0.04</td>
<td>26</td>
</tr>
<tr>
<td>Inorganic nitrogen</td>
<td>26</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total ammonia (mg/L)</td>
<td>&lt;LOD–0.37</td>
<td>0.04</td>
<td>0.08</td>
<td>17</td>
</tr>
<tr>
<td>Nitrate-N (mg/L)</td>
<td>&lt;LOD–9</td>
<td>2.62</td>
<td>2.75</td>
<td>26</td>
</tr>
<tr>
<td>Nitrite-N (mg/L)</td>
<td>&lt;LOD–0.3</td>
<td>0.02</td>
<td>0.07</td>
<td>2</td>
</tr>
<tr>
<td>Dissolved oxygen (mg/L)</td>
<td>0.21–20</td>
<td>8.87</td>
<td>4.71</td>
<td>1</td>
</tr>
<tr>
<td><strong>Biological water quality responses</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aquatic macroinvertebrate family richness</td>
<td>7–22</td>
<td>15.3</td>
<td>4.3</td>
<td></td>
</tr>
<tr>
<td>(total no. families)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Decomposition (proportion of initial weight lost)</td>
<td>0.19–0.93</td>
<td>0.50</td>
<td>0.21</td>
<td></td>
</tr>
<tr>
<td>Daphnia survival (no. test individuals alive of 10)</td>
<td>5–9</td>
<td>6.6</td>
<td>1.2</td>
<td></td>
</tr>
<tr>
<td>Daphnia reproduction (avg. mean no. neonates/individual/day)</td>
<td>1.95–5</td>
<td>3.17</td>
<td>0.81</td>
<td></td>
</tr>
<tr>
<td><strong>Landscape predictors (%) cover</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Forest</td>
<td>0–34</td>
<td>9</td>
<td>9</td>
<td></td>
</tr>
<tr>
<td>High-intensity crop</td>
<td>5–86</td>
<td>55</td>
<td>20</td>
<td></td>
</tr>
<tr>
<td>Edge</td>
<td>2–6</td>
<td>4</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>

Note: Agrichemical values < LOD were set to zero in statistical analyses.
duplicate using solid-phase extraction to achieve lower limits of detection prior to analysis. All analyses were performed on a high-performance liquid chromatograph (1200 Series, Agilent Technologies) with a tandem mass spectrometer (API 5000 Triple Quadrupole Mass Spectrometer and Turbo V™ Ion Source, AB Sciex). Details of all analytical methods and quality assurance are provided in the online Supplemental material. The limits of detection for atrazine and glyphosate were 0.0004 μg/L and 0.025 μg/L, respectively. The limits of detection for the neonicotinoids were 0.00025 μg/L for clothianidin and imidacloprid, 0.0002 μg/L for thiamethoxam, and 0.0001 μg/L for acetamiprid. Acetamiprid was not detected in any of the samples. We summed the mean concentrations of clothianidin, imidacloprid, and thiamethoxam for a given site to obtain a total neonicotinoid concentration (as in Main et al., 2015), as these compounds have similar structure and predicted additive toxicity (Morrissey et al., 2015).

Water samples were analyzed for inorganic nitrogen at Cadence Environmental Laboratories in Ottawa, following standard methods of the Environment Laboratory Services Branch of the Ontario Ministry of the Environment. Samples were stored in plastic bottles at 4 °C until analysis. Total ammonia (NH₃–N and NH₄–N) was determined by Colourimetry (method E3364), and nitrate-nitrogen (NO₃–N) and nitrite-nitrogen (NO₂–N) were determined by ion chromatography (method 4110 C) (Ontario Ministry of the Environment, 2010). Detection limits were 0.01 mg/L for total ammonia and 0.1 mg/L for nitrate-nitrogen and nitrite-nitrogen.

2.3.2.2. Leaf litter decomposition experiments. We determined the weight loss of leaf litter enclosed in mesh bags and exposed to water in ditches for one month as an assessment of decomposition rate in each ditch, where faster rates of decomposition generally indicate healthier aquatic systems (Gessner and Chauvet, 2002; Mathews and Kowalczewska, 1969). During the first water collection period (see above) in June, we submerged a 20 cm by 20 cm, 1-mm mesh bag containing 3 g of air-dried (for 2 weeks) mixed deciduous leaves, in each of the 27 ditches. The bags were placed in spots where they would remain fully submerged and minimally disturbed. We retrieved bags after one month during the second collection period in July. We kept bags chilled to prevent further decomposition during transit to the laboratory where they were immediately processed. In the laboratory, we removed all the leaf litter from each bag and gently rinsed the leaf litter with distilled water to remove sediment before oven drying (60 °C for 24 h; as in Fernández et al., 2016) to obtain dry weight. We used the proportion of initial weight lost as a measure of decomposition rate. The bags from two sites were not retrieved and these sites were therefore excluded from statistical models that involved decomposition (see Section 2.4 below).

2.3.2.3. Ceriodaphnia dubia bioassays. We measured population responses of an indicator species, the daphnia Ceriodaphnia dubia, to ditch water exposure in 27 laboratory bioassays, to determine if survival or reproduction responded to agrichemicals in ditch water samples. For this we used water collected during the June sampling period. Bioassays followed whole effluent chronic toxicity test guidelines for C. dubia (Environment Canada, 2007). We obtained a stock culture of C. dubia from Environment Canada at the beginning of May 2014, and established and maintained cultures to produce C. dubia neonates for testing (Environment Canada, 2007). We kept all cultures and experiments in a walk-in environmental chamber at 25 ± 1 °C, 40% humidity, and a daily photoperiod of 16 ± 1 h light and 8 ± 1 h dark. We gave daily feedings of cultured algae (Pseudokirchneriella subcapitata) and a standard mixture of yeast, alfalfa, and trout chow (Environment Canada, 2007). Each eight-day bioassay consisted of recording C. dubia survival and reproduction in 10 replicates of 15 mL of undiluted ditch water using a single C. dubia female neonate <24 h old in each replicate. The 10 neonates selected for each bioassay were within 12 h of the same age and reared in uncontaminated water that best matched the water hardness level (moderate vs. hard) of each tested ditch water sample. We renewed test solutions daily and during this time recorded any mortalities and the number of neonates produced per test individual. Our survival variable was the total number of test individuals (of 10) alive at the end of each bioassay. Our reproduction variable was calculated for each 8-day bioassay as the average number of offspring produced per live individual (n ≤ 10), per day.

2.4. Statistical analyses

To avoid over-fitting our statistical models, we reduced the number of agrichemical variables using principal components analysis (PCA), to linearly combine correlated variables. We performed two PCAs, one to produce a composite variable for pesticides (combining mean atrazine, mean glyphosate, and mean sum of neonicotinoids) and the other to produce a composite variable for inorganic nitrogen (combining total ammonia and the sum of nitrate-nitrogen and nitrite-nitrogen). All agrichemical variables were square-root transformed to normalize distributions and homogenize variances prior to statistical analyses. Agrichemical levels reported as less than the limit of detection (LOD) were set to 0, as in Balestrini et al. (2016).

We tested our predictions (Fig. 2) using confirmatory path analysis (Shipley, 2000, 2009) because it easily accommodates small to moderate sample sizes and count data. This allowed us to simultaneously model the direct and indirect relationships between the landscape predictors and our water quality measures. Forest and crop cover, and field edge amount, were predictor variables in our model; however, forest cover and edge amount were also defined as responses to crop cover because the amount of a landscape in forest cover and edge amount is constrained by the amount of crop cover. As described above, seven water quality response variables were included in the path model: an index of pesticide amount; an index of inorganic nitrogen amount; mean dissolved oxygen (mg/L); aquatic macroinvertebrate family richness; leaf litter decomposition amount; C. dubia survival; and C. dubia reproduction.

We used the directional separation test to evaluate the correlational structure of our hypothesized path model before parameterizing individual paths between variables (Gonzalez-Voyer and von Hardenberg, 2014; Shipley, 2000). The directional separation test involved testing each implied independency (i.e. every pair of variables predicted to lack a direct relationship) in the path model in a linear or generalized linear model to determine the probability that each pair was statistically independent (conditional on the hypothesized predictors in Fig. 2). The correlational structure of the full path model was then tested by combining all the probabilities using Fisher’s C statistic:

\[ C = -2 \sum_{i=1}^{k} \ln(p_i) \]
and comparing the resulting $C$ value to a chi-square distribution with $2k$ degrees of freedom, where $k$ = the total number of independencies (Shipley, 2000).

After determining that the correlational structure of the path model fit the data, we obtained individual path coefficients for the hypothesized paths by fitting a series of linear or generalized linear models for each response variable in the path model (Fig. 2). Aquatic macroinvertebrate family richness and number of surviving $C. dubia$ were modeled as count data using generalized linear models with a Poisson distribution and log-link function, and the other 7 response variables were modeled using linear models.

We further used a model selection approach (Burnham and Anderson, 2002) using Akaike’s information criterion corrected for small sample sizes (AICc) to evaluate the statistical support for individual hypothesized paths in the full path model (Fig. 2). For each of the nine response variables we created a set of candidate models comprised of a global model (i.e. the model containing all predictors hypothesized to influence the response; Fig. 2), an intercept-only (null) model, and all submodels derived from the global model. We considered a predictor to have strong support if it was in the top (lowest AICc) model. We considered a predictor to have weak support if it was included in the top model set (within 2 AICc units from the top model) but not included in the top model. In addition, if the null model was not the top model but was within in the top model set we considered predictors in the top model to have weak support. All analyses were conducted in R (R Core Team, 2018). Model selection was performed using the package AICcmodavg (Mazerolle, 2017). Prior to model selection we assessed the fit of all global models by examining residual plots. Residuals did not appear to violate assumptions of error distribution or homogeneity.

We assessed the potential influence of multicollinearity by examining the Pearson correlation coefficients between all pairs of predictors and calculating the Variance inflation factors (VIF) for each predictor in each model. Pairwise correlations between predictor variables in the path model were all <0.6 (Appendix A, Table A1) and the variance inflation factors for each predictor in each model were all <3 (Appendix A, Table A2). These values are below accepted maximum collinearity thresholds for estimating independent effects of predictors ($r < 0.7$; Dormann et al., 2013, and VIF < 5; Zuur et al., 2007).

3. Results

Descriptive statistics for the ditch water quality and land cover variables measured from the 27 landscapes are in Table 1. Agrichemicals were detected in water collected from every site. Atrazine was the most common agrichemical in ditch water, and the highest concentration for one site exceeded the maximum level of the Canadian water quality guidelines for the protection of aquatic life (1.8 µg/L; CCME, 1999a). Nitrate nitrogen concentrations from eight sites exceeded the long-term exposure maximum level for the protection of aquatic life (3.0 mg/L; CCME, 2012). Ten sites exhibited DO concentrations below the lowest acceptable levels for the protection of aquatic life stages in warm water ecosystems (6 mg/L; CCME, 1999b). We identified 54 families of aquatic macroinvertebrates representing 16 orders across the 27 ditches. The gastropod family Physidae was the most common taxon, present in 25 sites (Appendix B).

The first component of the pesticide PCA accounted for 58% of the variation and was comprised of strong positive loadings (>0.6) for all three pesticide variables (Appendix C, Table C1). The first component of the PCA of the nitrogen variables accounted for 61.7% of the variation in the nitrogen data, with equal loadings of 0.78 for both total ammonia and nitrate-nitrogen + nitrite-nitrogen (Appendix C, Table C2).

The $C$ value calculated from the independency tests (Appendix D) was 45.9 with $2k = 48$ degrees of freedom, resulting in a null probability of 0.56. This indicates that the data fit the hypothesized patterns of independence implied by the model (Fig. 2). Results of the tests of hypothesized paths are in Appendix E. Path coefficients and paths with statistical support are shown in Fig. 4. Our analyses supported two of our hypothesized linkages between landscape composition and water quality, and one of our hypothesized linkages between landscape configuration and water quality (Fig. 5): (i) a negative relationship between pesticide levels and the proportion of forest cover in the landscape (composition), (ii) a positive relationship between nitrogen levels and the proportion of high-intensity crop cover in the landscape (composition), and (iii) weak support for a positive relationship between macroinvertebrate richness and the proportion of edge cover in the landscape (configuration). Our analyses also supported three links among the water quality indices (Fig. 6): (i) weak support for a negative relationship between dissolved oxygen and nitrogen levels, (ii) a negative relationship between macroinvertebrate richness and nitrogen levels, and (iii) a positive relationship between macroinvertebrate richness and oxygen levels. These results also demonstrate three indirect negative effects of high-intensity crop cover and one indirect negative effect of nitrogen on macroinvertebrate richness: high-intensity crop cover indirectly impacts richness through a direct positive association with nitrogen and a direct negative relationship with edge, and both crop cover and nitrogen indirectly negatively affect richness through high-intensity crop cover increasing nitrogen levels, and nitrogen decreasing oxygen levels (Fig. 4). Leaf litter decomposition and $C. dubia$ survival and reproduction did not show strong responses to any predictor variables.

4. Discussion

Our results confirm that the water quality of small farm wetlands is influenced by the surrounding landscape (Fig. 4). Pesticide levels decreased as forest cover increased in the surrounding landscape, and inorganic nitrogen increased with increasing amounts of high-intensity crop cover (Fig. 5). These results are consistent with previous studies that have examined relationships between water quality of water bodies and the surrounding land cover within circular buffers (Declerck et al., 2006; Koumaris and Fahrig, 2016) or within watersheds (Gonzales-Inca et al., 2015; Liu et al., 2012). We also found evidence that the amount of crop cover in the landscape indirectly decreases oxygen levels and aquatic macroinvertebrate richness, through increasing nitrogen levels in ditches (Figs. 4 and 6). Together, the results are consistent with the hypothesis that forest cover reduces agrichemical loads in runoff through chemical uptake and transformation, while agricultural cover is a nonpoint source of agrichemicals to surface waters. We did not find support for the hypothesis that increasing landscape configurational heterogeneity, i.e. increasing field edge cover, reduces agrichemical inputs to farmland ditches (Fig. 4). This is in contrast to studies that found positive relationships between water quality and edge density in the landscape (Uuemaa et al., 2005; Uuemaa et al., 2007; Liu et al., 2012). However, some previous results are mixed (Gémési et al., 2011; Lee et al., 2009; Li et al., 2015). We suggest that the lack of effect of edge cover on water quality in our study is likely due to the very flat topography of our region, combined with the widespread use of tile drainage in the crop fields. Tile drains can bypass subsurface water flows beneath strips of native vegetation, preventing the interception of water by plant roots and opportunities for filtration and uptake, and discharging directly into surface waters (Blann et al., 2009). This could negate potentially beneficial effects of field edges on water quality in farmland in our region. It is possible that edges have stronger positive effects on water quality in regions without tile drainage than regions with tile drainage. Testing this post-hoc hypothesis would require further research.

While landscape composition measures were the strongest predictors of water quality in ditches, we also found some support for an association between water quality and landscape configuration: aquatic macroinvertebrate family richness was positively related to field edge cover in the surrounding landscape (Figs. 4 and 5). This result is in line with previous work suggesting that increasing configurational
heterogeneity in agricultural landscapes can increase biodiversity (Collins and Fahrig, 2017; Fahrig et al., 2015; Flick et al., 2012; González-Estébanez et al., 2011; Holland and Fahrig, 2000; Monck-Whipp et al., 2018; Novotný et al., 2015). For example, the richness of some terrestrial insect groups has been positively associated with edge density (Novotný et al., 2015), patch density (Flick et al., 2012), and the amount of woody borders (Holland and Fahrig, 2000) in agricultural landscapes, and insect diversity can be negatively related to mean crop field size (González-Estébanez et al., 2011; Fahrig et al., 2015). Our results suggest the same is true for aquatic insects in agricultural landscapes and is consistent with the hypothesis that field edges benefit some taxa by providing habitat and facilitating movement through the landscape.

Taken together, the lack of effect of configurational heterogeneity on agrichemical inputs and the positive effect of configurational heterogeneity on biodiversity suggest that different management guidelines will be needed for the provision of different ecosystem services in farmland. Services such as pollination and biological pest control, which are provided by terrestrial and semi-aquatic species (Orford et al., 2015; Saha et al., 2012) will benefit from decreasing crop field sizes and increasing edge density in the landscape (Hass et al., 2018). As noted by Fahrig et al. (2015), this can be accomplished without taking land out of production. In contrast, services such as the breakdown of agrichemicals and the maintenance of water quality in farmland wetlands in our region will require land use guidelines that limit the total cover of high intensity agriculture and maintain the cover of more natural areas such as forests. If, as we speculate above, the lack of edge effect on agrichemicals is due to subsurface drainage bypassing edge vegetation, it may also be possible to decrease agrichemical pollution of ditch water by restricting drain discharge through controlled tile drainage (Sunohara et al., 2015) or saturated riparian buffers (Jaynes and Isenhart, 2014).

We did not find support for the prediction that aquatic macroinvertebrate richness would be positively associated with the proportion of the landscape in forest cover. We had hypothesized, based on previous studies (Didham et al., 2012; Jonsen and Taylor, 2000), that forest cover in the surrounding landscape would facilitate movement and provide habitat for the terrestrial stages of some invertebrates. However, while some invertebrate groups respond positively to forest cover in the landscape, others can respond negatively (Frisch et al., 2016). It may be that shrubby cover (typical of field edges) is used by more semi-aquatic invertebrate taxa than forest cover as terrestrial habitat in farmland, which is consistent with our positive effect of edge cover and lack of effect of forest cover.

Our results suggest that aquatic macroinvertebrate family richness is strongly impacted by fertilizer use in our study region through direct and indirect pathways. Invertebrate richness decreased with increasing nitrogen levels in ditches (Figs. 4 and 6). Richness was also indirectly negatively related to nitrogen levels (and thus also to high intensity crop cover), through a negative effect of nitrogen on dissolved oxygen levels (Figs. 4 and 6). These relationships are consistent with the results from previous studies (Wang et al., 2007; Yuan, 2010). Elevated levels of inorganic nitrogen can induce toxic effects on many aquatic organisms, and also result in eutrophication, leading to harmful hypoxic or anoxic conditions (Camargo and Alonso, 2006). Considering that one third of our ditch sites had nitrate-nitrogen levels that exceeded the maximum long-term exposure level for the protection of aquatic life, it is not surprising that we found direct and indirect negative effects of nitrogen enrichment on invertebrate richness. Based on these results, we recommend that reducing nutrient losses in runoff should be a primary goal of farmland water conservation initiatives in our region. Again, this could potentially be achieved by implementing management practices that reduce contaminant inputs from tile drain discharge (Jaynes and Isenhart, 2014; Sunohara et al., 2015).

Fig. 4. Observed relationships among landscape predictors, physicochemical water quality variables, and biological water quality responses in 27 drainage ditch transects. Landscape predictors (square-root transformed forest cover, arcsine transformed high-intensity crop cover, and edge cover), were measured in 1-km radius landscapes surrounding each transect. Results for all predicted paths from Fig. 2 are shown. Paths with strong statistical support are represented by thick solid arrows, paths with weak support are represented by thin solid arrows, and paths without support are shown as dashed arrows (analytical results in Appendix E). Standardized path coefficients were derived from the global model for each response.
Surprisingly, we found no relationship between macroinvertebrate family richness and pesticide levels in ditches (Fig. 4). This is in contrast to studies that found negative effects of pesticide contamination on stream aquatic invertebrate richness (Beketov et al., 2013; Orlinskiy et al., 2015), and to research demonstrating negative effects of sublethal pesticide exposure on invertebrates (Russo et al., 2018). A possible explanation for our result is that there may be at least one species within each family that is tolerant to the pesticide levels in our ditches (e.g. Shahid et al., 2018), and so the loss of intolerant species would not result in a decrease in family richness. This explanation was also suggested by Ieromina et al. (2016), who describe an intriguingly similar result to ours: a nutrient (phosphate) was the most important predictor structuring invertebrate communities, assessed by the composition of functional traits, in agricultural ditches, while pesticides had no effect. They speculated that communities may adapt to pesticide stress through sensitive species being replaced by tolerant ones with similar functional traits, thus maintaining community trait composition.

Aquatic macroinvertebrate richness was a more sensitive water quality indicator than leaf litter decomposition or C. dubia population responses in bioassays. While macroinvertebrate richness responded to physicochemical water quality, leaf litter decomposition and C. dubia reproduction and survival did not (Fig. 4; Appendix E). Previous studies suggested that decomposition and C. dubia population responses should be sensitive indicators of water quality (Baldy et al., 2007; Eagleson et al., 1990; Medeiros et al., 2008; Piscart et al., 2009). For example, fungal decomposition of leaf litter in aquatic environments can be inhibited in low oxygen conditions (Medeiros et al., 2009), and by nutrient enrichment (Baldy et al., 2007; Piscart et al., 2009). However, it has also been suggested that aquatic decomposer diversity can be reduced in contaminated waters without changes to decomposition rates, due to community shifts to fewer tolerant species (Pascoal et al., 2005). Additionally, moderate eutrophication in streams has been shown to accelerate decomposition, presumably by added nutrients stimulating fungal activity (Gulis et al., 2006). Regarding the lack of effects on C. dubia, it is possible that increases in food resources in ditch water with elevated agrichemical levels compensated for any negative toxicological effects. For example, García-García et al. (2012) suggested that elevated levels of organic matter in agricultural stream water may have augmented the diet of C. dubia in laboratory bioassays, leading to increases in fecundity. Thus, our results call into question the use of leaf litter decomposition and of C. dubia population responses in bioassays as general indicators of water quality in farmland wetlands.

5. Conclusions

Our results suggest that landscape management to improve farmland water quality should focus on the composition of the landscape, in particular, increasing amounts of non-crop cover such as forest, and reducing amounts of crop cover associated with high agrichemical inputs. These landscape composition predictors were strongly related to agrichemical levels in ditches, and indirectly related to aquatic macroinvertebrate richness. In contrast, landscape configurational heterogeneity (measured as the amount of field edge cover), was positively associated with aquatic macroinvertebrate richness, but unrelated to

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**Fig. 5.** Relationships between landscape variables and water quality measures from 27 agricultural ditches. (a) Pesticides (a linear combination of square-root transformed mean atrazine, square-root transformed mean glyphosate, and square-root transformed summed mean clothianidin, imidacloprid, and thiamethoxam) vs. proportion of forest cover (square-root transformed) in the surrounding 1-km radius landscapes. (b) Inorganic nitrogen (a linear combination of square-root transformed total ammonia and square-root transformed nitrate-nitrogen + nitrite-nitrogen) vs. proportion of high-intensity crop cover (arcsine transformed) in the surrounding 1-km radius landscapes. Shaded areas represent 95% confidence intervals. (c) Aquatic macroinvertebrate family richness vs. proportion of field edge cover in the surrounding 1-km radius landscapes.
agrichemical levels. These results imply that increasing configurational heterogeneity as a management plan for terrestrial biodiversity will also benefit aquatic macroinvertebrate diversity, but will not greatly benefit physicochemical water quality, at least in our region where tile drainage is common. The possibility that configurational heterogeneity may have stronger effects on physicochemical water quality in regions without tile drainage requires further study. Our results have practical implications for landscape management because the spatial extent in which we quantified relationships between landscape structure and water quality (1-km radius landscapes) is relevant for individual farm management. Based on our results, we recommend the creation of agri-environmental programs that encourage the preservation and enhancement of forest cover, and the reduction of crop cover associated with high chemical inputs to improve farmland water quality.

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Appendices A-E and supplementary information for analytical methods

Appendices A–E and supplementary information for analytical methods to this article can be found online at https://doi.org/10.1016/j.scitotenv.2018.11.400.

Fig. 6. Relationships among water quality variables measured in 27 agricultural ditches. (a) Mean dissolved oxygen (mg/L) vs. inorganic nitrogen (a linear combination of square-root transformed total ammonia and square-root transformed nitrate-nitrogen + nitrite-nitrogen). (b) Aquatic macroinvertebrate family richness vs. inorganic nitrogen. (c) Aquatic macroinvertebrate family richness vs. mean dissolved oxygen (mg/L). Shaded areas represent 95% confidence intervals.

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