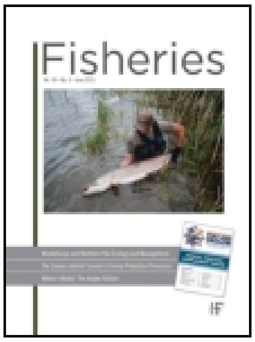

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Smartphones Reveal Angler Behavior: A Case Study of a Popular Mobile Fishing Application in Alberta, Canada

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FEATURE

Smartphones Reveal Angler Behavior:

A Case Study of a Popular Mobile Fishing Application in Alberta, Canada

Successfully managing fisheries and controlling the spread of invasive species depends on the ability to describe and predict angler behavior. However, finite resources restrict conventional survey approaches and tend to produce retrospective data that are limited in time or space and rely on intentions or attitudes rather than actual behavior. In this study, we used three years of angler data from a popular mobile fishing application in Alberta, Canada, to determine province-wide, seasonal patterns of (1) lake popularity that were consistent with conventional data and (2) anthropogenic lake connectivity that has not been widely described in North America. Our proof-of-concept analyses showed that mobile apps can be an inexpensive source of high-resolution, real-time data for managing fisheries and invasive species. We also identified key challenges that underscore the need for further research and development in this new frontier that combines big data with increased stakeholder interaction and cooperation.

Teléfonos inteligentes revelan comportamiento de pescadores: el caso de estudio en Alberta, Canadá, de una aplicación para teléfono móvil

El manejo exitoso de las pesquerías y el control de la dispersión de especies invasivas depende de la habilidad para describir y predecir el comportamiento de los pescadores. Sin embargo, la limitación de recursos restringe el uso de muestreos convencionales y tiende a producir datos históricos incompletos en tiempo y espacio, y se fundamenta en intenciones o actitudes más que en el comportamiento real de los pescadores. En este trabajo se utilizan tres años de datos sobre pescadores obtenidos mediante una aplicación para teléfonos móviles en Alberta, Canadá, para determinar, a nivel provincie, los patrones estacionales de: 1) popularidad del lago de acuerdo a los datos convencionales, y 2) conectividad antropogénica del lago que no ha sido ampliamente descrita en Norteamérica. El análisis para poner a prueba el concepto mostró que las aplicaciones para teléfono celular pueden representar una fuente de datos barata, de alta resolución y que opera en tiempo real para manejo de pesquerías y de especies invasivas. También se identificaron retos clave que resaltan la necesidad de realizar investigación en el futuro y desarrollar información acerca de esta nueva frontera tecnológica que combina grandes cantidades de datos y mayor interés y cooperación por parte de los inversionistas.

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INTRODUCTION

Anglers and angler regulations determine the magnitude, distribution, and timing of fishing within a region. Therefore, the ability to predict angler behavior can provide insight into multiple stressors such as exploitation, the potential spread of aquatic invasive species, and fish diseases (Drake and Mandrak 2010). Accordingly, both successful fisheries management and invasive species control depend on the ability to quantify and forecast angler behavior (Buchan and Padilla 1999; Muirhead and MacIsaac 2005; Hunt et al. 2011).

Typically, angler behavior is quantified through a variety of empirical approaches (e.g., creels, diaries, interviews, mail surveys) that vary widely in effort, cost, and efficacy (Fenichel et al. 2013; Griffiths et al. 2013). However, these approaches tend to produce retrospective data that are limited in time or space and often reveal intensions or attitudes rather than actual behaviors (Adamowicz et al. 1994). The amount of data generated using these approaches is also limited by decreasing budgets (Riecke et al. 2013).

Mobile smartphone applications (apps) are a novel approach to collecting scientific data. As of January 2014, the percentage of American adults who owned a smartphone was 85% for ages 18–29, 79% for ages 30–49, 54% for ages 50–64, and 27% for ages 65+ (Pew Research Center 2015). Similarly, app use has increased dramatically in the last decade, and global app downloads are predicted to surpass 100 billion by 2015 (Dufau et al. 2011; Edvinsson 2013). Cellular and wireless coverage are

Where other tools require a project to be launched, along with the need to train and motivate volunteers, apps can collect data passively.

also broad, and smartphones come standard with GPS, accelerometers, gyroscopes, and high-resolution digital cameras. This combination of mobility and measurement capability makes apps ideal for citizen science (Newman et al. 2012). Relevant examples include botany (BudBurst[M]), entomology (Journey North), ornithology (BirdLog), and wildlife (Moose Hunter Survey). (Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.)

Although smartphone usage and the number of science-based apps have grown significantly, the use of apps for fisheries science remains limited, especially in recreational fisheries (Gutowsky et al. 2013). Notable exceptions include iAngler, which is generating data in support of Common Snook *Centropomus undecimalis* stock assessments in Florida (Muller and Taylor 2013); International Game Fish Association Catchlog, which is currently in beta testing in Everglades National Park, Florida (IGFA 2014); iFishWatcher, which is generating fisheries data in Europe (Abou-Tair et al. 2013); and iSnapper, which for-hire vessel captains in Texas are using to generate real-time harvest data for Red Snapper *Lutjanus campechanus* (Stunz et al. 2014). Researchers in North Carolina are also experimenting with a text-based data collection system for coastal recreational anglers (Baker and Oeschger 2009).

The limited use of fishing app data by management agencies and the fisheries community in general is surprising given that these data essentially represent volunteer angler diaries in digital format. Diaries can be biased, but they are also a low-cost, high-resolution form of data collection that can inform multiple fisheries management topics (reviewed by Cooke et al. 2000). Fishing apps have the added benefit of providing fine-scale movement data, platforms for on-demand angler surveys, opportunities for real-time communication and interaction, and ease of distribution and collection. In addition, where other tools require a project to be launched, along with the need to train and motivate volunteers, apps can collect data passively. For example, a recent study found that passive data from a similar medium (an online angler forum) predicted spatial and temporal patterns of fishing effort in Nebraska reservoirs (Martin et al. 2014). Therefore, fishing apps represent an underutilized tool for efficiently collecting information on angler behavior and other data relevant to fisheries management and invasive species control.

Fishing apps are particularly suited to generating data pertaining to the spread of aquatic invasive species and fish diseases. These phenomena are increasing in both scale and frequency (MacIsaac et al. 2004; Bain et al. 2010) and can be important to sustainable fisheries management (Dextrase and Mandrak 2006; Faisal et al. 2012). Apps allow for rapid reporting and detection (e.g., MISIN 2014) and have the added benefit of generating movement data that reveal transmission pathways and trends, and ultimately inform prevention and response efforts.

This study describes a proof-of-concept analysis involving three years of existing app data that were generated by anglers in Alberta, Canada. We are particularly interested in province-wide, seasonal patterns of lake popularity and angler movement in the context of aquatic invasive species and fish diseases. More generally, this case study serves to (1) illustrate the available potential of fishing app data, (2) highlight key issues and challenges, and (3) identify future applications and research directions.

METHODS

App Data and Filtering

We obtained user-generated data from the iFish Alberta smartphone app for the period December 2010 to January 2014. This app is developed and distributed by The App Door of Edmonton, Alberta, Canada. The app provides anglers with fishing-related information for more than 700 lakes in Alberta, which represent over 90% of all managed lakes (Environment and Sustainable Resource Development [ESRD] 2014). The app also collects user-generated data (henceforth "records") in the form of hotspot logs, catch logs, ice reports, and lake reports. A hotspot record is created when a user enters the date, time, and geographic location of a catch. Similarly, a catch log record is created when a user enters information pertaining to a fish caught (e.g., species, length, location). An ice report record is created during the ice-fishing season when a user shares information about ice conditions, and a lake report record is created when a user shares lake-specific information related to fishing (e.g., types, sizes, and quantities of fish caught). Associated with each record are a unique and anonymous user identification number, a lake identification number, a date/time stamp, and text that the user has entered.

To first determine the relative popularity of lakes in Alberta, we filtered for those records that appeared to indicate that a user visited a specific lake on a specific date (henceforth "visits"). Because a visit is implied when a user records a hotspot, logs a catch, or reports on ice conditions, we assumed that most of these record types were authentic. Exceptions were redundant records and records unrelated to fishing (as identified by user text). Due to the conversational nature of lake reports, however, we did not assume that all lake report records indicated actual lake visits. Many lake report records within the data set were discursive, consisting of chatter about technique, regulations, lake access, or text not related to fishing. Therefore, we individually assessed the text associated with each lake report record and filtered out those that did not indicate an actual visit to a specific lake. Because users often recorded their lake reports subsequent to their visit, we also filtered out all records that indicated a visit more than a week prior to the recorded entry. Thus, any lake report time stamp in our filtered data was likely to be accurate to within seven days.

Analysis of App Data

We used the frequency of both visits and records summed over lakes to determine popularity among Alberta lakes and the extent to which unfiltered records gave a reliable signal for visits (Pearson correlation). We then interpolated filtered frequency data by season to generalize seasonal patterns of angler distribution in relation to population centers and principle highways. For seasons, we coded each visit as either open water fishing (May to November) or ice fishing (November to April) according to approximate ice-on and ice-off dates that we estimated from ice report records. Spatial interpolation was via inverse distance weighting (cell size = 1.6 decimal degrees, power = 1, fixed radius, points = 0, distance = 2.2 decimal degrees).

To assess the anthropogenic connectivity of lakes in Alberta in the context of the spread of aquatic invasive species, we identified all instances of the same user visiting two lakes within seven days and then summed across users. The result was a

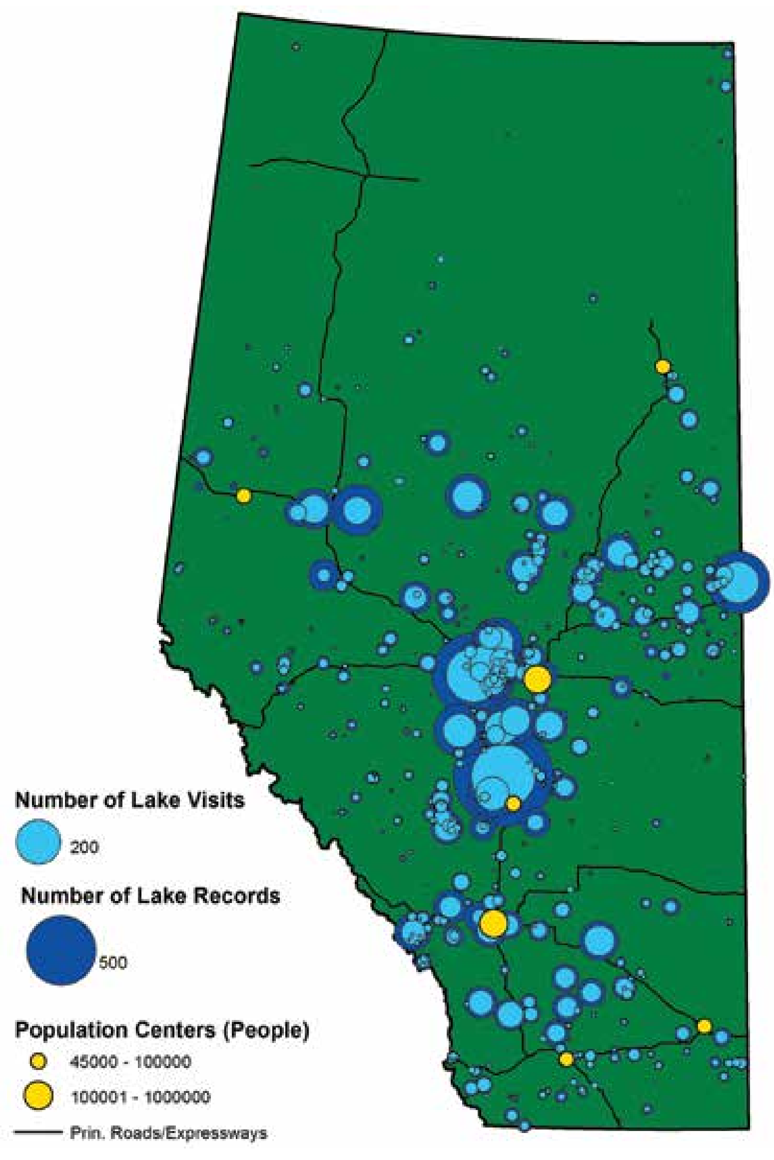

Figure 1. Popularity of lakes in Alberta and their proximity to population centers and principle transportation infrastructure according to 12,268 lake records generated by 2,827 users (unfiltered data) and 6,004 lake visits by 2,358 users (filtered data).

number of spatial connections of varying degree (i.e., cumulative visit frequency) between pairs of lakes. The seven-day window has been shown to be a critical period for the spread of aquatic invasive species and fish diseases relevant to Alberta (Ricciardi et al. 1995; Havel and Stelzleni-Schwent 2001; Hawley and Garver 2008). Therefore, anthropogenic connectivity in this study is a proxy for likely pathways of species invasion among Alberta lakes.

Comparison to Conventional Data

We used simple linear regression to compare the frequency with which app users visited Alberta lakes (seasons combined) to the popularity of Alberta lakes as revealed by two Alberta ESRD data sets. We first compared app-based visits in summer to the number of angler visits as estimated by the most recent ESRD summer creel survey data that were available. Survey details are given in M. G. Sullivan (2003). This analysis was restricted to those lakes for which we had both creel and app data. The second analysis compared the annual percentage of total app-based visits within each of Alberta's 10 fish management watershed units to the annual percentage of total angling effort within these units as determined by a voluntary mail-in survey that was conducted in 2010 (Zwickel 2012). We forced each regression through the origin because it was reasonable to assume that the absence of anglers visiting a lake or watershed unit precludes a subset of these anglers (i.e., app users) from visiting that lake or watershed unit. No angler movement data were available to validate our estimates of anthropogenic connectivity. All statistical analyses were performed in R version 2.15.1 (R Core Team 2012), and all spatial analyses were performed in ESRI ArcMap version 10.0. (Redlands, CA).

RESULTS

Lake Popularity

Between December 2010 and January 2014, 2,827 app users (~1.3% of active resident anglers in Alberta; DFO 2012) generated over 12,000 records by logging hotspots and catches and submitting ice reports and lake reports. Nearly half of all records (6,004 records from 2,358 users) appeared to indicate that a user visited a specific lake on a specific date. Across all 497 Alberta lakes that were visited by app users, records and visits were highly correlated (Pearson correlation, $r = 0.99$, $P < 2.2e\text{-}16$). Both showed that the most popular lakes among app users were concentrated around the Edmonton census metropolitan area (CMA), the Calgary CMA, and the Calgary–Edmonton corridor (Figure 1). Other areas of modest lake popularity included several of the provincial parks and recreation areas within recreational driving distance of Edmonton (e.g., Cold Lake and Lesser Slave Lake provincial parks). Despite the Calgary CMA having a slightly higher population and approximately the same number of nearby (albeit smaller) lakes, both records and visits were much lower than in the Edmonton CMA.

Seasonally interpolated visit data also showed that app users preferred lakes near the Calgary–Edmonton corridor and the

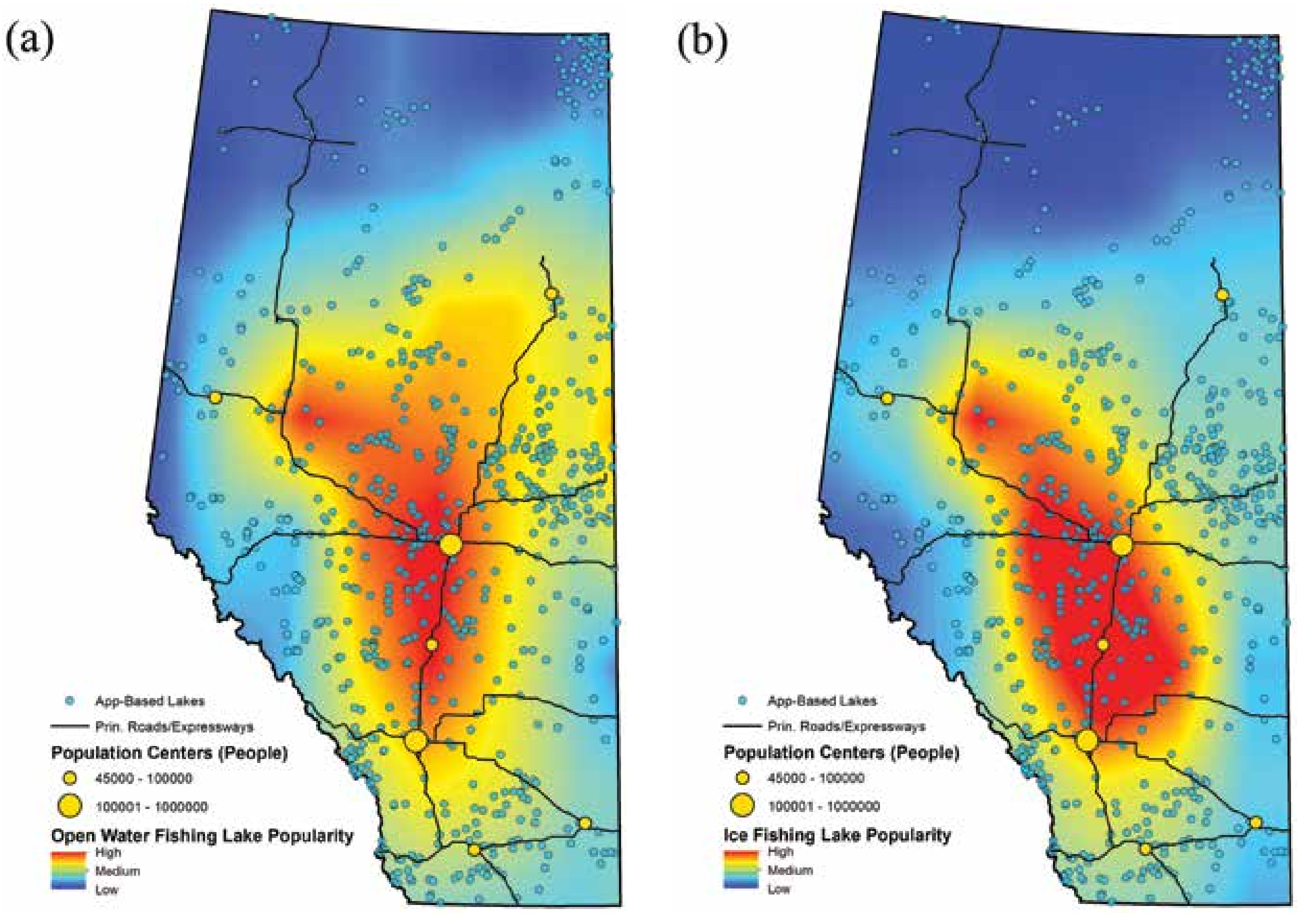

Figure 2. Seasonal popularity of lakes in Alberta for open water fishing: (a) 2,986 visits to 362 lakes by 1,431 users and ice fishing (b) 3,013 visits to 289 lakes by 1,222 users.

regions northwest and northeast of Edmonton and that this pattern was highly influenced by population centers and infrastructure (Figures 2a, 2b). This pattern also varied seasonally in that app users preferred lakes closer to population centers in winter, whereas app users were more likely to visit lakes in the east-central region of the province during the open-water season.

Anthropogenic Connectivity

We identified 1,246 instances where an angler visited two Alberta lakes within a seven-day window. A majority (57%, although not significant) of these trips occurred during the ice fishing season. In both seasons, approximately 80% of trips were less than 150 km in Euclidean distance (centroid to centroid). The frequency of trips greater than 300 km (4.3%), though uncommon, was still significant. Combined, these anthropogenic connections formed a network that was similar in pattern to the distribution of lake popularity (Figures 1, 2), with most connections located around or near population centers and transportation infrastructure (Figures 3a, 3b). The influence of population centers and transportation infrastructure was particularly evident in winter. However, in both seasons we observed several connections that were isolated from the larger network. For example, app users who fished Laurier Lake in Whitney Lakes Provincial Park in winter also tended to fish nearby Stoney Lake (linear distance of 38.2 km) in the same week.

Comparison to Conventional Data

We found a linear relationship between the frequency of app-based visits in summer and the number of angler visits as estimated by summer creel surveys on 36 Alberta lakes (Figure 4). The linear relationship was significant ($r^2 = 0.74$, $F_{1,35} = 99.7$, $P = 8.81e\text{-}12$) and implied that, on average, app visits underestimated total angler visits by a factor of approximately 254. We also found a linear relationship between the percentage of app visits by watershed unit and the popularity of these watershed units, according to the 2010 survey (Figure 5). This relationship was also significant ($r^2 = 0.82$, $F_{1,8} = 40.8$, $P = 2.12e\text{-}4$) but not significantly different from the 1:1 line. However, app data tended to overestimate the relative popularity of the Parkland Prairie 2 watershed unit (i.e., Edmonton CMA) and underestimate the popularity of the Eastern Slopes 1 watershed unit (i.e., Calgary CMA).

DISCUSSION

Our analysis of data from a popular fishing app revealed both annual and seasonal patterns of lake popularity and anthropogenic lake connectivity. The former were consistent with conventional data, and both analyses revealed patterns at spatial and temporal scales that are impractical with conventional survey methods. In this section, we discuss our results in the context of

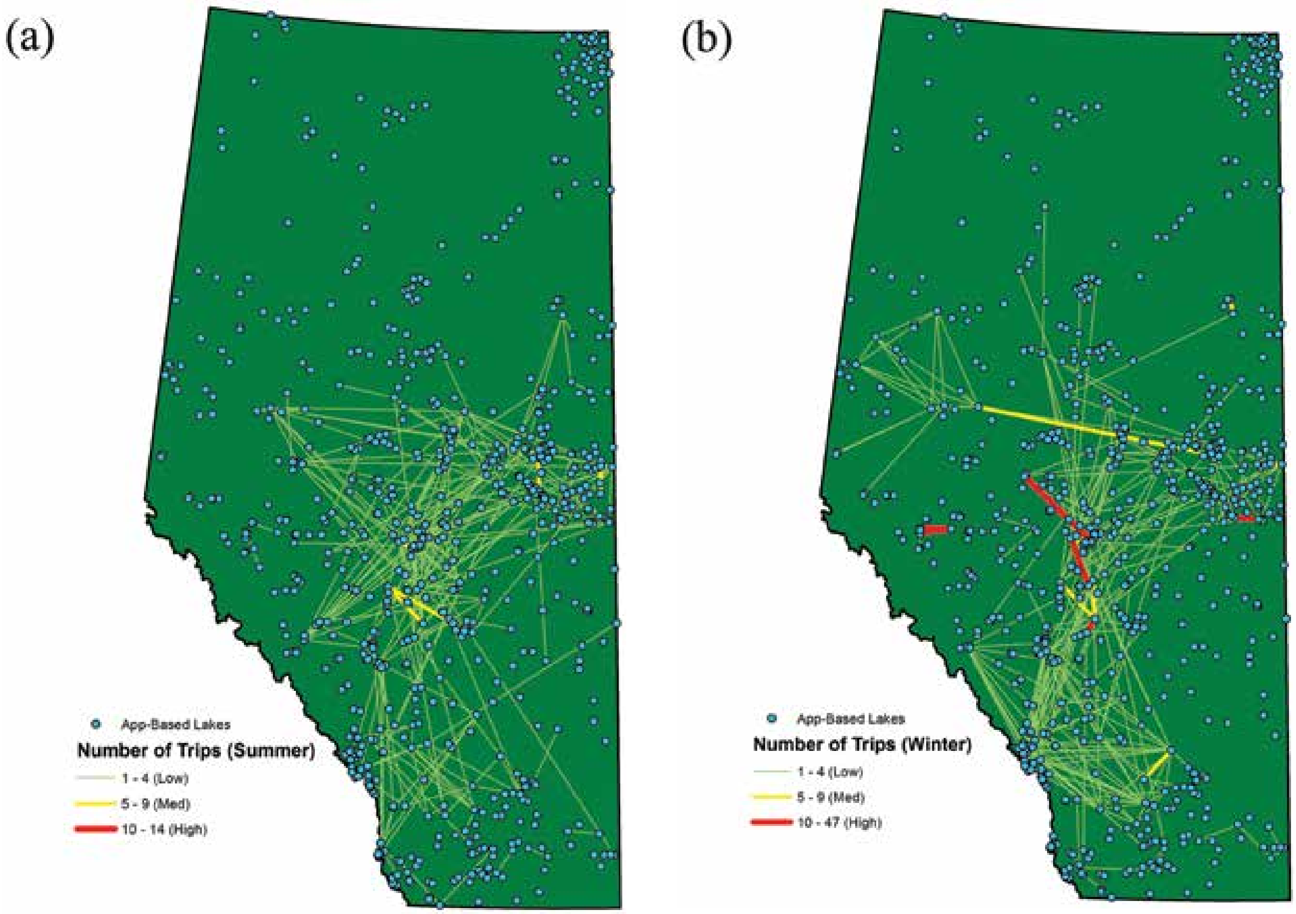

Figure 3. Seasonal anthropogenic connectivity of lakes in Alberta for open water fishing: (a) 304 low-, 7 medium-, and 1 high-strength connections and ice fishing: (b) 293 low-, 10 medium-, and 8 high-strength connections.

the spread of invasive species, expand this discussion to include broader applications of app data to fisheries, and identify some of the challenges and next steps for working with app data.

App Data and the Spread of Invasive Species

Our results demonstrate that app data can address the need for timely, inexpensive, and high-resolution information regarding the vectors and dispersal pathways of aquatic invasive species and fish diseases. Anglers and their equipment are significant vectors for the dispersal of many aquatic species (Johnson et al. 2001; Cameron et al. 2007; Drake and Mandrak 2014), and understanding how (and why) anglers move about the landscape is crucial to understanding and controlling the spread of invasive species and identifying critical control points, such as high-frequency linkages of lake connectivity. Consequently, several approaches to understanding angler movement patterns have emerged in recent decades. Mathematical approaches have included such methods as gravity and transportation network modeling (Leung et al. 2006; Drake and Mandrak 2010), and empirical approaches have focused mainly on survey methods (Buchan and Padilla 1999; Muirhead and MacIsaac 2005).

Although it is possible to derive networks from surveys and interviews, networks derived from app data would be easier to obtain, include more lakes, and show how invasive species transmission risk varies seasonally and changes over time.

App data can contribute to our understanding of angler movement in a number of ways. First, app data are observational and therefore likely to expose the revealed preferences of anglers. This is in contrast to conventional survey data (which reveal stated preference and are usually retroactive) and simulation models (which predict preference but can be data-hungry, assumption-rich, and difficult to validate; Nicholls 1989; Johnston et al. 2010). When combined with information on the location of infected waterways, these revealed preferences might better inform invasive species risk assessments. Second, app data reveal anthropogenic connectivity. Information about which lakes anglers travel between, in addition to which lakes they travel to, is a significant step forward in elucidating potential pathways of transmission of aquatic invasive species and fish diseases. For example, the hypothetical introduction of dreissenid mussels into popular and well-connected areas such as the Calgary–Edmonton corridor might pose a much greater risk to Alberta's aquatic resources than an introduction into less popular and poorly connected areas such as the southeast corner of the province. Although it is possible to derive networks from surveys and interviews, networks derived from app data would be easier to obtain, include more lakes, and show how invasive species transmission risk varies seasonally and changes over time. For example, formal analyses of the seasonal networks in Alberta (e.g., Junker and Schreiber 2008) are likely to reveal the distribution and direction of lake connections and show how connections vary seasonally and are influenced by lake characteristics such as area, species composition, watershed development, and proximity to population centers and other lakes. Third, app data are unique in that they are available at fine spatial and temporal resolutions over broad spatial and temporal scales. Data collection by apps is largely limited, not by fiscal resources but by the number, frequency, and distribution of app users. Finally, whereas conventional surveys reveal angler behavior at discrete points in space and time, app data are continuous and can therefore reveal patterns over seasons, years, months, or even days. This flow of real-time data will help managers to quickly and effectively plan for and respond to the detection and spread of aquatic invasive species and fish diseases.

Benefits and Broad Applications

In general, high-resolution, real-time app data offer exciting opportunities to explore long-term and spatially broad trends in angler demographics, behavior (e.g., individual/group home ranges), and harvest as well as responses to regulation changes, disease outbreaks, fish kills, and stocking events. Information can also feed back onto agencies (i.e., adaptive management) and anglers instantly, providing lake-specific estimates of fishing pressure or harvest relative to a fisheries reference point. App data are also likely to complement, and in some cases provide a viable alternative to, conventional lake and angler surveys. For example, our analyses show that app data predict survey-based estimates of angler effort in most regions of Alberta as well as creel-based estimates of angler visits to specific Alberta lakes (see also Martin et al. 2014). The latter relationship was less strong, perhaps because creel data preceded app data by up to 19 years. Because surveys, creels, and other conventional methods are relatively expensive, time consuming, and limited in space and time, substituting or supplementing with app data might allow agencies to allocate their resources more efficiently. In order to realize these efficiencies and avoid redundant efforts and issues with data compatibility, we recommend that agencies collaborate to develop apps or app standards.

Social network analysis could also be applied to app data to reveal patterns of social engagement and connectivity. Recent studies have demonstrated the importance of social networks in both the exploitation and conservation of fisheries resources (e.g., Mueller et al. 2008). Anglers comprise coupled socioecological systems in that they relate to and interact with each other, lake ecosystems, and management. Socioecological systems in general have been the focus of much study in the past decade (Liu et al. 2007; Hunt et al. 2011; Schlueter et al. 2012), and apps could provide another tool for furthering this research and transforming it into effective policy. For example, a social network analysis of app data could help to identify which angler groups are most likely to bring together diverse segments of a network to facilitate collective action around a problem such as invasive species (Prell et al. 2009 and references therein).

Finally, mobile apps represent a significant opportunity for the development of citizen science approaches within fisheries. Citizen science approaches provide a cost-effective means of collecting continuous data over large spatial scales (Cohn 2008). To date, we are aware of only two published examples of apps that were designed specifically for citizen science: one for watershed monitoring (Kim et al. 2011) and the other for ornithology (Sullivan et al. 2014). The number of recreational anglers in

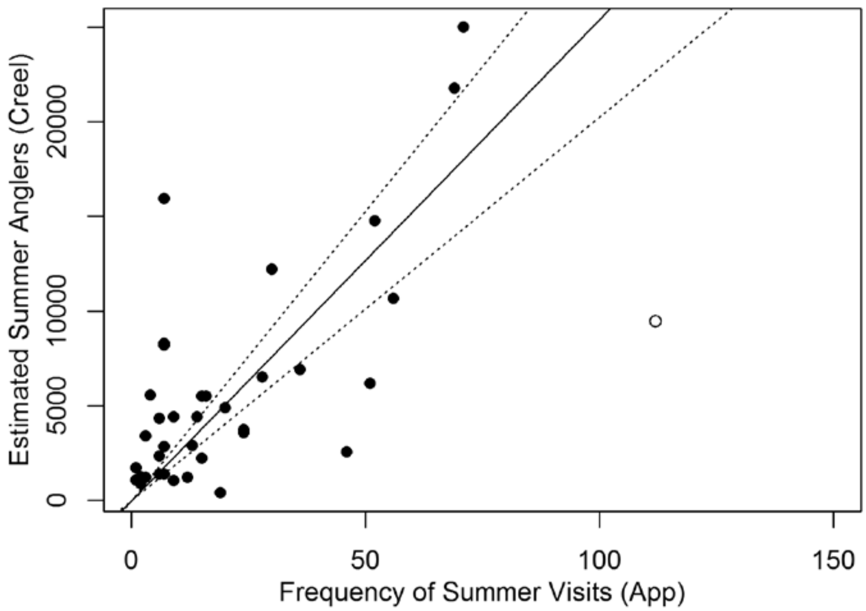

Figure 4. Scatterplot of ESRD summer creel survey data for 36 popular Alberta lakes (1995–2012) versus the frequency of app-based summer visits to these lakes. The solid line is the linear regression line forced through the origin (slope = 254.0 estimated angler visits per app user visit). Dotted lines are 95% confidence intervals for the regression line, and the open circle is an influential outlier (Lake Wabamun) that we excluded from the analysis.

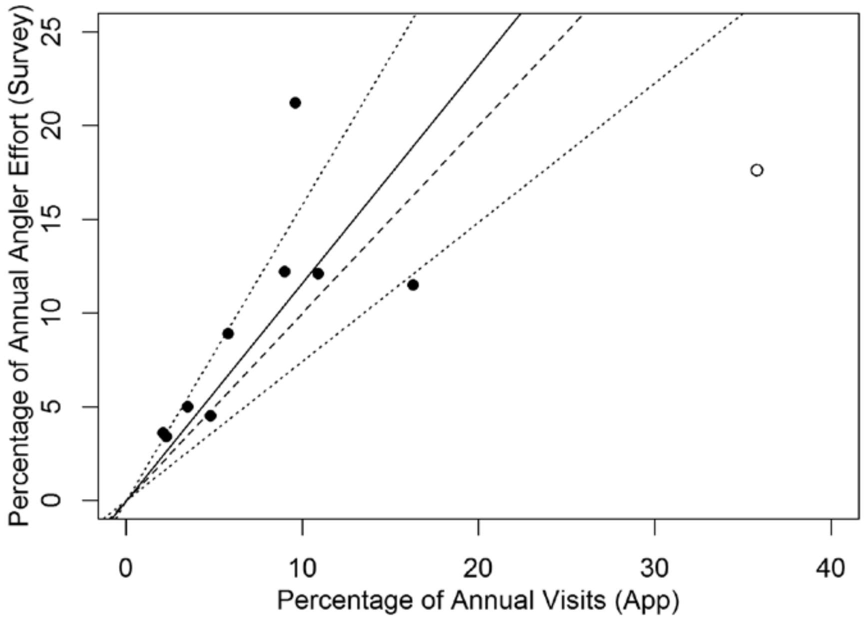

Figure 5. Scatterplot of the percentage of total angling effort in Alberta by fish management watershed unit versus the percentage of total app-based visits by fish management watershed unit. The dashed line is the 1:1 relationship, the solid line is the linear regression line forced through the origin (slope = 1.16), and dotted lines are 95% confidence intervals for the regression line. The open circle is an outlier (Parkland Prairie Zone 2) that we excluded from the analysis.

many regions of the world (e.g., >36 million in Canada and the United States; DFO 2012; USDOI et al. 2011) represents a large and mostly untapped resource for fisheries science and management. Specially designed apps (or features within existing apps) could be developed and deployed in citizen science contexts to provide fisheries researchers with information on a diversity of topics including the distribution and occurrence of species of interest, the occurrence of outbreaks of fish diseases, and the timing and duration of fish migrations and spawning.

Challenges and Next Steps

Properly designed apps are a source of high-resolution, real-time, and cost-effective data that can be utilized in fisheries management and science; however, there are challenges to collecting app data of sufficient quality. One challenge is that app data are subject to unique forms of bias. For example, our analysis of relative popularity within Alberta's fisheries management watershed units showed decreased lake popularity near Calgary and increased lake popularity near Edmonton, relative to a conventional survey. These discrepancies are likely due to our app data not including riverine locations, which are abundant along the Eastern Slopes region of Alberta but were not included in the app until after our analysis. Sampling bias may also help to explain why app data underestimated angler effort in some Alberta lakes (e.g., Pigeon Lake, Lesser Slave Lake) and overestimated in others (e.g., Gull Lake, Wabamun Lake) (S. Spencer, Alberta Environment and Sustainable Resource Development, personal communication). Thus, an understanding of any inherent biases that result from app design and user demographics is essential prior to making inferences about an angler population.

Other sources of bias in app data include transiency (the short-term use of an app) and avidity (a small number of users creating a disproportionate amount of data). In our study, for example, ~ 7% of the users that downloaded the app generated location data. Of these users, 37% generated 75% of that data. These challenges underscore the importance of design requirements that facilitate the ease and enjoyment of app use. Biases associated with reporting (e.g., anglers exaggerating catches) and avoidance (due to lack of agency trust or a reluctance to share) are also likely to cause inaccuracy in the context of app-based data collection. Therefore, fisheries scientists might initially focus on validating app-based data collection methods by comparing apps with creel and mail-based methods (the current standards) as well as comparing app user demographics against angler demographics. If demographic bias is unavoidable, then fisheries scientists can, as a minimum, determine what segment(s) of the angler population app data represent.

Where specific forms of bias can complicate the collection of app data, noise filtering can also complicate its analysis. Noise filtering of user-generated text is a common challenge, particularly in social media contexts (Aggarwal and Zhai 2012). Variance is typically larger with user-generated text data; consequently, preprocessing techniques have been developed to improve data quality. These techniques span a wide spectrum of complexity and efficacy, and obtaining high-quality data can be challenging (Agichtein et al. 2008). Filtering approaches are context dependent in that they depend on the question or pattern of interest. Therefore, each new question requires a different set of assumptions, which complicates the task of defining and identifying noise. For example, analyzing our data set for the relative popularity of freshwater game fishes would have required a completely different filtering approach than the one used. Haphazardly applying filters can result in the inclusion of low-quality data, reducing the power of the analysis. Conversely, overfiltering the data can result in the exclusion of high-quality data and lead to collective patterns of behavior that are not consistent with individual preferences (Zafarani et al. 2014). In our study, filtering of the text-based data resulted in the reduction of over 50% of the total records. Therefore, in the interest of reducing noise and improving efficiency, apps could be designed with specific data needs and analyses in mind.

CONCLUSIONS

Fishing apps are broadly applicable to research, facilitate regular monitoring, and improve the efficiency, spatial and temporal extents, and resolution of conventional survey methods. But with only a few notable exceptions (e.g., Sweeney 2011; Presley 2012), fisheries science lags behind other fields and disciplines in the development and use of app technology (Gutowsky et al. 2013). Our finding that anglers visited lakes that were within a reasonable driving distance of large population centers is nothing new; it is consistent with conventional data from Alberta and well established in the literature (e.g., Post et al. 2008; Ward et al. 2013). However, the fact that we observed angler preferences (and movement networks) by applying fairly basic analyses to data from the uncoordinated use of an app that was not developed for research demonstrates the enormous potential of this technology. Fully realizing this potential could be achieved by (1) developing and/or modifying apps for research; (2) being aware of the biases inherent in and limitations to analyzing app data; (3) conducting more formal ecological, social, and coupled system analyses; and (4) exploring novel applications. To this end, we encourage coordinated research and agency collaboration to improve the application and use of these technologies alongside and even in place of existing data collection methods, particularly when trying to understand complex angler behaviors that determine harvest, distribute revenue, and control the spread of invasive species and diseases.

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