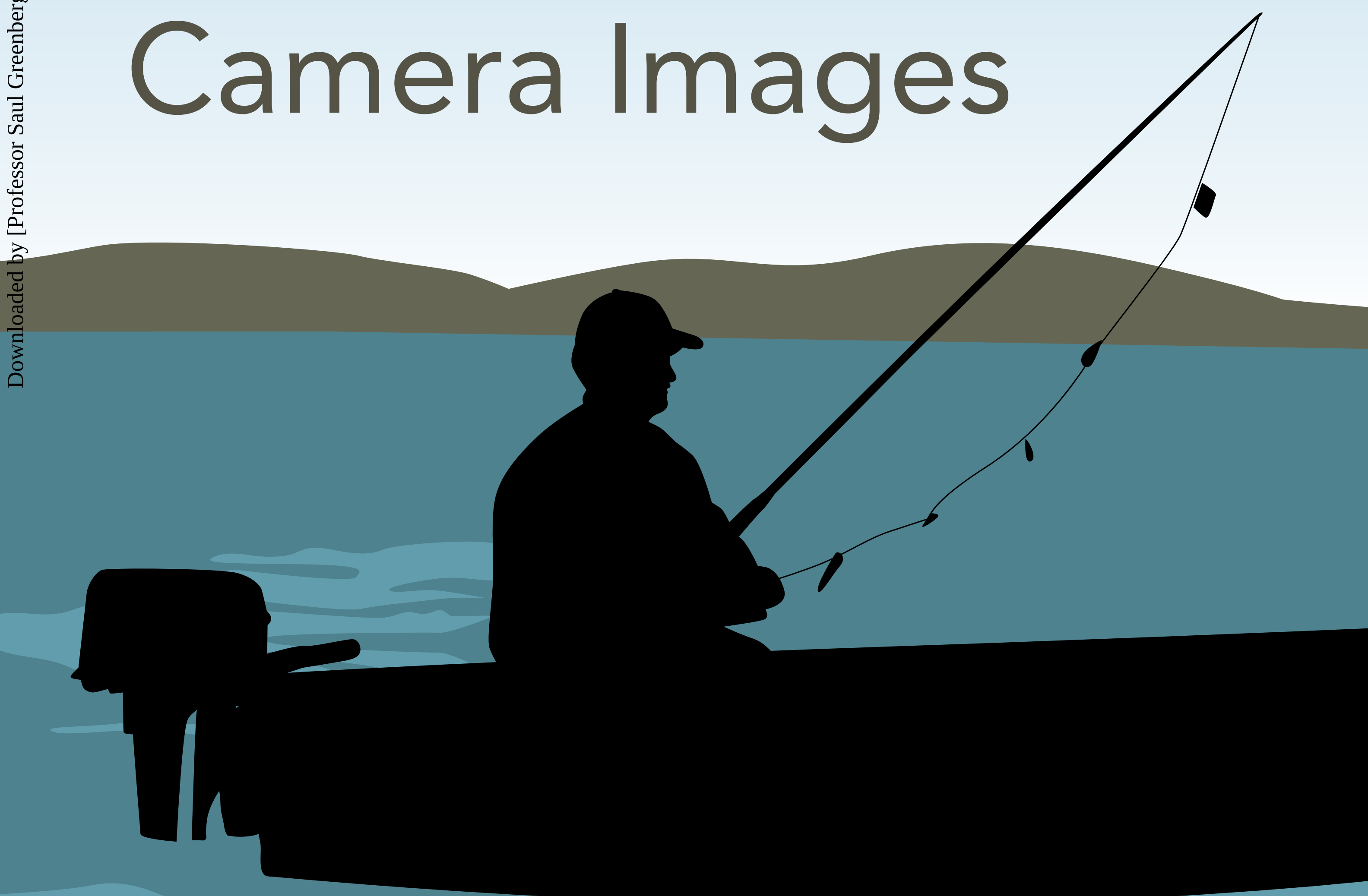
FEATURE

A Tool Supporting the Extraction of Angling Effort Data from Remote Camera Images



Estimating angling effort on more than a few lakes can be prohibitively expensive using creel surveys and often requires finer-scale angler distribution data than aerial surveys can provide. An alternate method uses remote cameras to capture images of lakes at hourly intervals over long time periods. Technicians then visually analyze the thousands of generated images for features of interest (e.g., angler counts and environmental conditions) and use those data to estimate angling effort. The problem is that the visual analysis step is time-consuming, expensive, and difficult to validate. Consequently, we elicited the strategies and best practices technicians used when analyzing images and identified bottlenecks. We then designed software, called Timelapse to better support image analysis. In use for several years, Timelapse has proven a cost-effective method of estimating angling effort in British Columbia's small lakes fisheries; it significantly eases a technician's workflow and doubles the number of images one can process per hour.

Una herramienta de apoyo para la obtención de datos de esfuerzo pesquero mediante imágenes de cámara remota

La estimación del esfuerzo de pesca con anzuelo que se realiza en varios lagos mediante muestreos en puerto, puede llegar a tener costos prohibitivos y suele requerir una información más fina sobre la distribución del esfuerzo que la que proveen los muestreos aéreos. Un método alternativo se basa en la captura de imágenes de los lagos usando cámaras remotas, tomadas cada hora durante largos periodos. Posteriormente, los cientos de imágenes generadas son analizadas visualmente por los técnicos con el fin de detectar características de interés (v.g. conteo de pescadores y condiciones ambientales) y esta información se usa para estimar el esfuerzo de pesca. El problema es que el análisis visual consume mucho tiempo, es caro y difícil de validar. En consecuencia, en este trabajo se elucidan las estrategias y mejores prácticas que el personal técnico utiliza al analizar las imágenes e identificar cuellos de botella. Posteriormente se diseña un programa llamado Timelapse, como apoyo para el análisis de imágenes. Habiendo sido utilizado por varios años, Timelapse ha mostrado ser un método efectivo en cuanto a costos para estimar el esfuerzo en pesquerías de pequeños lagos en la Columbia Británica; alivia de forma importante el flujo de trabajo del personal técnico y duplica el número de imágenes que pueden procesarse en una hora.

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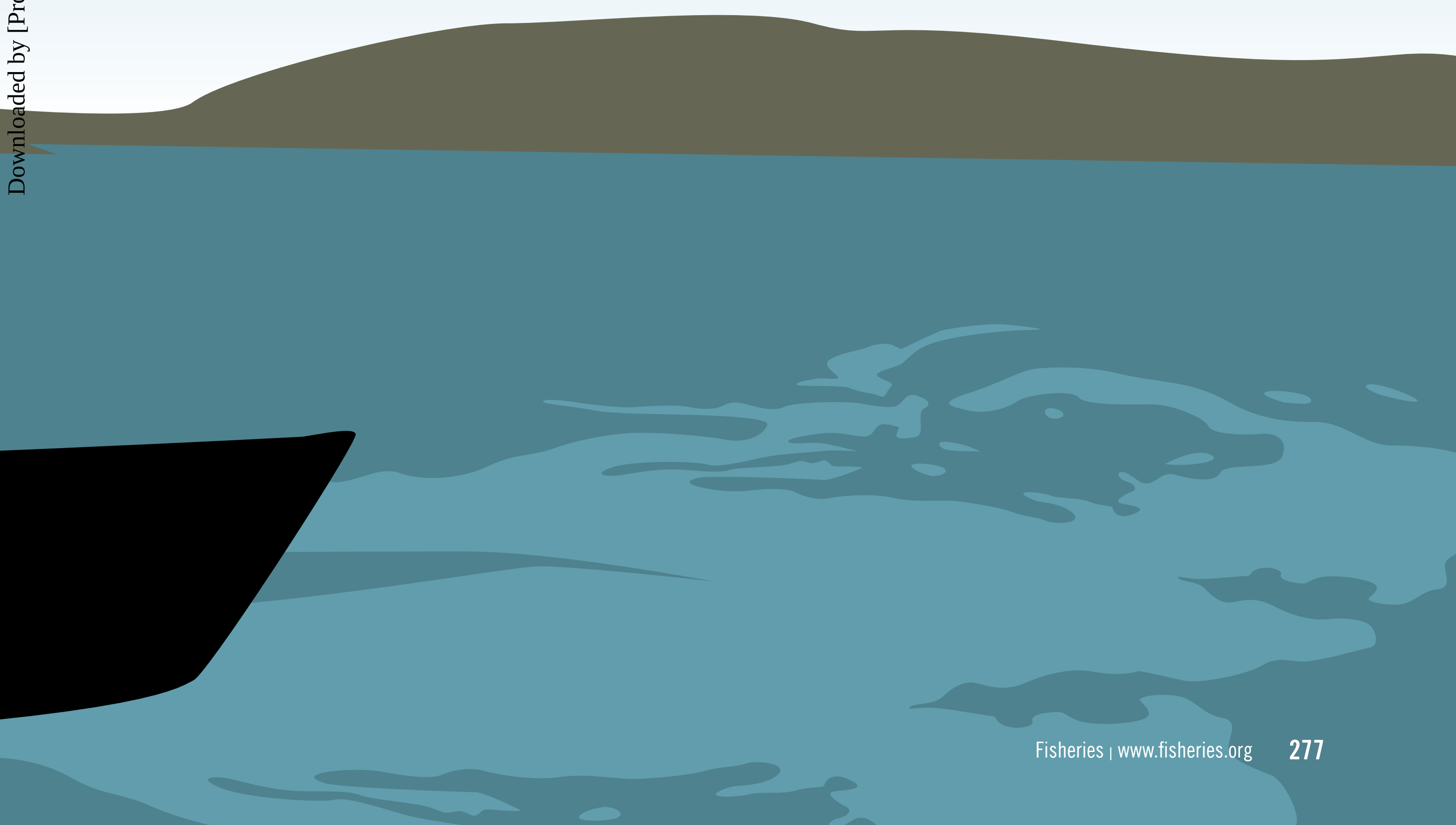


INTRODUCTION

Freshwater fishing effort is an important metric used by fisheries biologists to manage recreational fishing on small lakes, as is done in British Columbia (BC) and other open-access fisheries. Though managing such lakes can be done on a lake-to-lake basis, the mobility of anglers and the fiscal reality of decreasing resources make it increasingly important to manage lakes on a broader scale (Lester et al. 2003). Sustainable fishing effort is, of course, a primary performance measure for managing open-access recreational fisheries (Askey et al. 2013). As such, two strategies have been typically employed, either separately or collectively, to determine effort: aerial boat counts and creel surveys. However, a third new strategy is emerging, gathered by analyzing time-lapse images of lake activity as periodically captured by strategically positioned cameras. This article focuses on how technicians analyze those images for angler count data and how a software system called Timelapse supports their image analysis process.

Aerial boat counts can provide a standard index of angler activity for many lakes across a broad landscape over years (Tredger 1992; Parker et al. 2006). They can be cost effective when lakes in a flightline are geographically close (McGuiness et al. 2000). However, their costs can vary because the cost per lake is directly related to the frequency of sampling and the proximity of lakes within a flight path. For example, consider

Cameras are suitable for monitoring many lakes…remote and/or hard-to-access lakes, capturing winter effort…and daily and seasonal effort trends.

BC's use of aerial surveys over the past five years to collect angler counts on 113–274 lakes in two to five annual flightlines (36–99 lakes/flightline). The cost of aerial surveys varied between CAD$179 per lake in areas where lakes were geographically close and charter flights cheaper to CAD$635 in more remote areas where lakes were farther apart and flights more expensive (BC Small Lakes Committee, data on file). Another problem is that the instantaneous count of a relatively infrequent aerial survey done at a particular time of day may lead to highly variable estimates (Tredger 1992; Parker et al. 2006). For example, fishing activity as indicated by angler counts can vary by day (e.g., weekday vs. weekend), by proximity of a lake to a community (e.g., if a lake is close to a community, fishers tend to fish mostly in the evening vs. remote lakes where fishers are active throughout the day), and desired fish species (e.g., where certain species are fished at different times of the day; Parker et al. 2006). In contrast, stratified creel surveys provide more detailed information on specific fisheries, such as fine-scale temporal data (e.g., a.m. vs. p.m., weekday vs. weekend, and seasonal differences) and precise catch information. Their main disadvantage is that their cost limits the frequency and duration of the survey on a particular lake as well as the number of lakes that can be monitored. In some cases, the cost of a creel survey on a small lake can outweigh the value of the fishery (Parkinson et al. 1988).

A third strategy has been recently developed to help estimate angling effort: time-lapse remote field cameras. Though remote cameras have broad scientific use in wildlife research (Kays and Slauson 2008; O'Connell et al. 2011), they have only recently been applied to fisheries (van Poorten 2010; Smallwood et al. 2012). Cameras are strategically placed on lakes to repeatedly capture images over long time periods (e.g., months to years). Images are retrieved periodically. Technicians later analyze each image to visually extract angler count data as an index of relative effort, which in turn can be used to predict total angling effort (van Poorten 2010; van Poorten et al., pers. comm.). This approach has many advantages. Cameras can be a cost-effective way of providing angler counts (Parnell et al. 2010; Smallwood et al. 2012). Cameras are suitable for monitoring many lakes, monitoring remote and/or hard-to-access lakes, capturing winter effort (important because ice fishing can represent a significant proportion of resource pressure), and capturing daily and seasonal effort trends. In addition, camera data can be used alone or combined with data collected from the other two strategies to produce an even more accurate view of angling effort over time.

Using cameras to calculate fishing effort comprises four primary steps:

1. *Camera placement and image capture.* Cameras must be deployed to capture a reasonably broad field of view of a lake if they are to capture angler activity (Figures 1–3) while still producing images of sufficient fidelity for an analyst to visually detect and discriminate between objects of interest. Placement must also consider public concerns about privacy, where cameras should avoid capturing high-fidelity features of people. Technicians affix cameras to landscape features (typically trees) at one or more strategic locations surrounding a lake. Each camera is configured to repeatedly capture images over time—usually once every hour—for periods of weeks to months to years. Alternately, if placed at a lake's access point, image capture can be configured to use motion detection.
2. *Image retrieval and storage as an image set*. Technicians revisit cameras periodically, usually every 4 to 10 weeks, to change camera batteries, if necessary, and to retrieve the images. The biologist then stores the images from that camera into a folder, which is cataloged as an image set. Image sets are folders labeled by a unique name identifying a specific lake and date range of the images taken.
3. *Image analysis*. An analyst visually scrutinizes every digital image in an image set to obtain a total count of anglers (on shore, in boats, on ice). For each image, the analyst also encodes information such as the lake identification, time and date the image was captured, camera name, and environmental conditions. Particular features of interest vary with the study objective. Obtaining this information from images is the most time consuming part of the process. For example, a lake with only one camera set up to take a picture every hour will produce 8,760 images per year. Although cameras can be set up to take fewer images (e.g., to capture only particular time periods), the number of images remains significant, especially if numerous lakes are being monitored.
4. *Calculating recreational angling effort*. The above angler counts are then used to predict total angling effort, where they can also be calibrated against existing creel and aerial survey results if available (van Poorten 2010; Smallwood

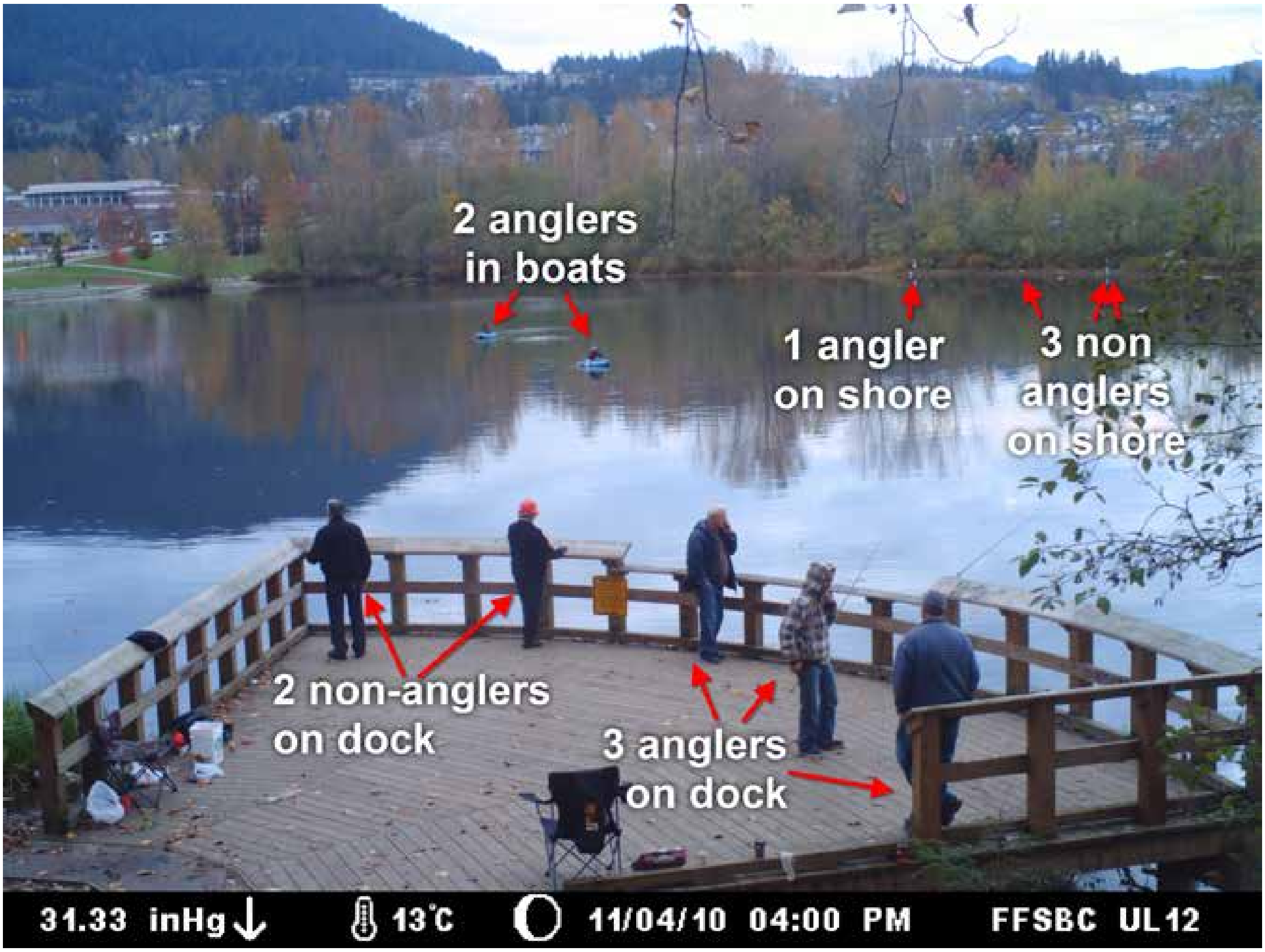


Figure 1. A high-effort urban lake with a remote camera capturing activities primarily around a dock.

et al. 2012; van Poorten et al. pers. comm.). Broadly speaking, the calculation requires a correction factor (which incorporates concurrent instantaneous counts of the total angler numbers on the lake at one time) because the camera's field of view may not capture all anglers on a lake. If instantaneous counts are unavailable, image counts are still useful for comparing relative effort trends across years.

A bottleneck in this process, and the focus of this article, is in the third image analysis step. Each image set consists of a large number of images—usually thousands—and there are a multitude of image sets. A single lake generates multiple image sets, where each image set represents a different time period and even different camera placements. Biologists are usually interested in numerous lakes. For example, BC currently monitors 75 small lakes throughout the province using 86 cameras set to take hourly images. This generates roughly several hundred thousand to more than half a million images per year, each of which must be systematically stored and hand-analyzed. The problem is that the image inspection and encoding step takes considerable time, is tedious and error-prone, and is hard to validate. The costs for analyzing images alone can make effort estimates obtained using cameras somewhat expensive.

Consequently, the Freshwaters Fisheries Society of BC decided to investigate and improve upon this important step. Our first goal was to understand the existing ad hoc image analysis process. We used a contextual inquiry method (Holzblatt et al. 2004), where we interviewed and stepped through the existing process with various analysts to uncover their strategies and to detect pinch-points. Our second goal was to develop a software tool to support the analysts' best practices, ideally resulting in an efficient image inspection and data encoding practice. As we will see, the same system could be used to verify the reliability of entered data and could be applicable to a broad range of other wildlife and fisheries related projects involving remote cameras.

STUDY SITES AND TYPICAL IMAGES CAPTURED

Our case study involves the 75 small lakes currently monitored by remote cameras in BC. These lakes differ in their physical, geographical, and fishery characteristics and range from 7 to 430 ha in size. Lake characteristics constrain camera placements, the type of image produced, and differences in fidelity of objects of interest. To illustrate this range, this section describes several typical study sites along with examples of captured images. These images also illustrate why image analysis can be difficult.

A High Effort Urban Lake: Camera Capturing Activities around a Dock

A dozen BC lakes are managed as urban lakes (i.e., a lake situated in a high-density urban area that receives considerable visitation). Urban lakes tend to be small (<50 ha). Most are heavily managed for multiple recreational activities (e.g., biking, dog walking, picnicking, and fishing). They often have access

Figure 2. A moderate-effort remote lake with a remote camera capturing roughly 50% of the lake surface and accessible shoreline.

points (e.g., parking and walkways), well-developed pathways around the shoreline (allowing fishing access from various points on the shore), and docks that further concentrate boating and fishing activities. Figure 1 is an image taken from a remote camera on a typical urban lake. The camera was positioned primarily to capture the concentrated angler activity on the dock and to include anglers on boats and the far shoreline.

A Low to Moderate Effort Remote Lake: Camera Captures Majority of Lake Surface and Accessible Shoreline

Most of BC's 1,083 regularly stocked lakes are in remote rural or wilderness areas. Access ranges from paved to 4 × 4 roads to walk-ins. Effort on these lakes is typically low to moderate, although effort estimates are still needed to understand the outcomes of management changes (e.g., access alterations and stocking prescription changes). Figure 2 illustrates a camera image from a typical remote lake. The camera was positioned to capture 50% of the surface area (for capturing boats) and the majority of accessible shoreline, including its campsite, boat launch, and primary access point (for capturing shore anglers).

A High Effort Winter Fishery: Camera Captures Commonly Fished Area of Ice Surface

In some lakes in northern regions, the four-month winter fishery represents a significant proportion of a lake's total effort. Yet, winter conditions mean that aerial surveys are not used, and creel surveys are only occasionally done. Figure 3 illustrates an image from a winter fishery camera, where it captures the most commonly fished area on the ice surface, including ice anglers, their companions and pets, and the equipment they bring to ease transport and fishing comfort. Ice fishing is often concentrated in hotspots so that a camera capturing 30% of the lake surface can capture more than 50% of the angling pressure.

Other Study Site Factors

Not all study sites precisely fit the above descriptions. For example, lake size is a significant factor. For somewhat larger lakes, biologists may use multiple cameras to increase the percentage of the lake area captured. One constraint is that instantaneous counts are still required for total effort calculations regardless of the estimate of the percentage surface area seen by the camera(s). Yet, for very large lakes (>450 ha) or lakes with multiple basins, a few cameras cannot capture a large enough proportion of anglers. Instead, cameras configured in motion detection mode can be placed at access points, including boat launches and trails, to estimate arriving and departing anglers or fishing hotspots. If accurate instantaneous counts cannot be done effectively, good estimates of total effort on such lakes cannot be calculated. Even so, angler counts can still act as a surrogate for angling pressure trends from year to year. Another significant factor is the data desired, where cameras can be positioned to best capture images that reveal other data on resource use, such

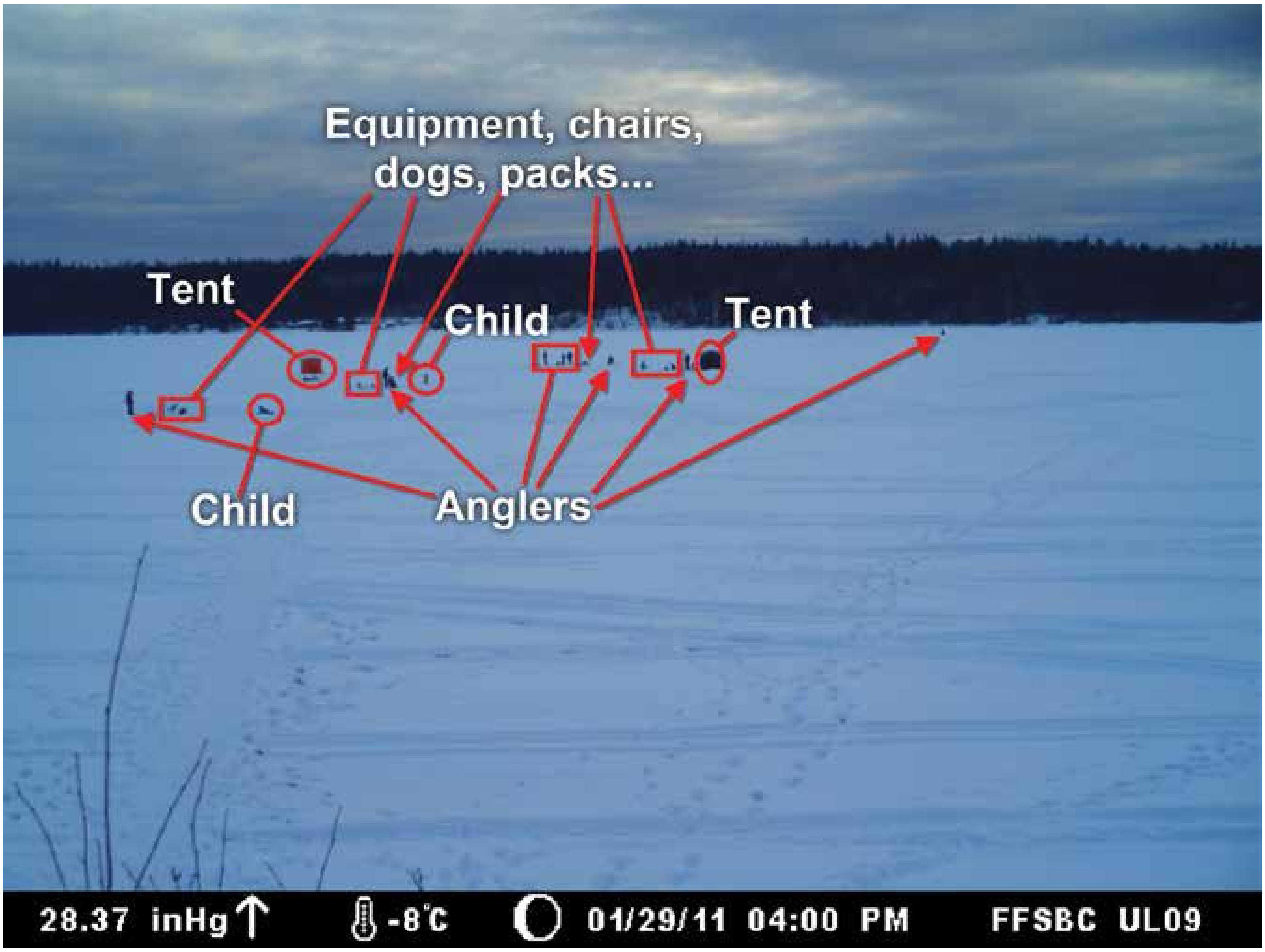


Figure 3. A high-effort winter fishery with a remote camera capturing the most commonly fished area on the ice surface. This image captures a mix of anglers at different locations and distances, fishing paraphernalia, pets, and children.

as demographics (e.g., gender and age group) and activities (e.g., biking and hiking). Finally, other agencies may have study sites and data needs that differ from the BC case study reported here, which will likely affect how they place cameras, the frequency and time length of image capture, and what image analysis is performed.

Mitigating Problems in the Image Analysis Process

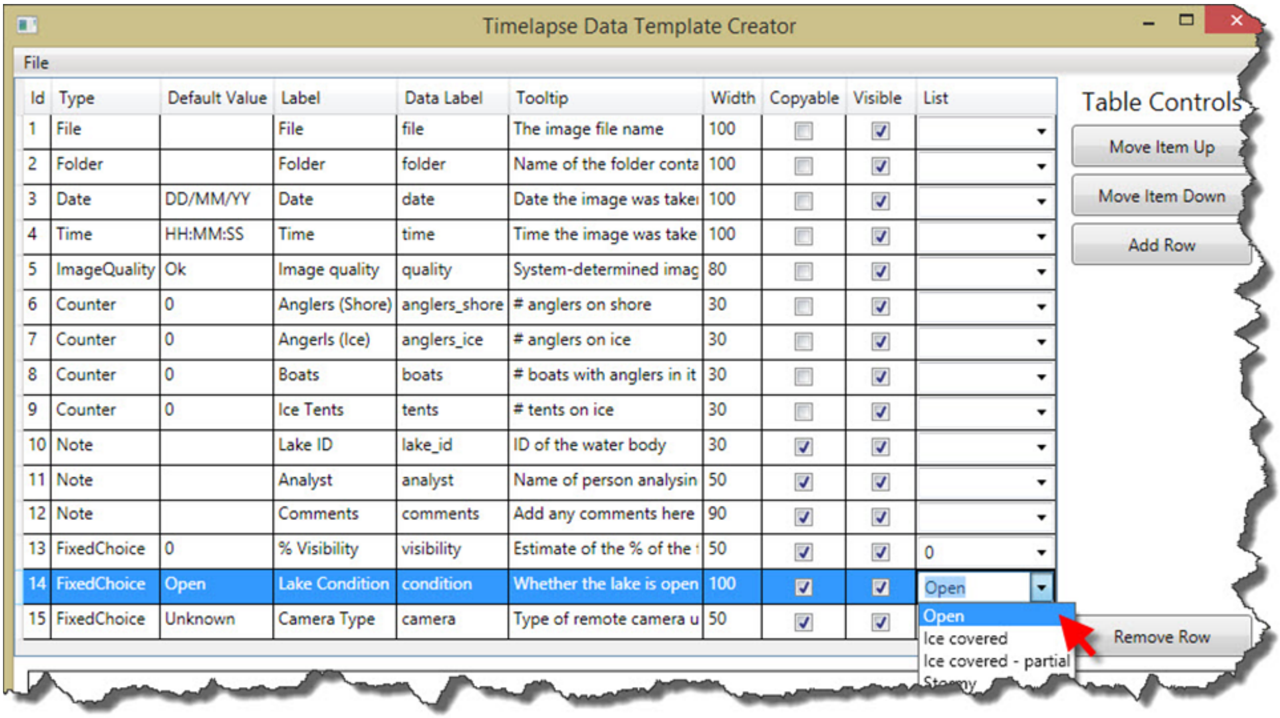
We walked through the original image analysis process (the spreadsheet method) with various analysts to uncover the strategies they were using, to itemize how they performed their tasks and to detect pinch-points. The spreadsheet method began with the biologist distributing image sets to analysts along with a Microsoft Excel spreadsheet template: each spreadsheet row represented a single image, and its columns indicated data categories. Using off-the-shelf photo software such as Microsoft PhotoViewer, analysts then inspected each image for various attributes and recorded any results in the corresponding spreadsheet row (e.g., date, time, anglers, boats, and environmental conditions). After completion, analysts returned the spreadsheet to the biologist for inspection.

Our walkthrough identified significant problems and inefficiencies. The spreadsheet method proved tedious and time-consuming. Data were fraught with errors and difficult to validate. Consequently, we designed Timelapse, an image analysis software tool that mitigates various workflow problems. Timelapse and tutorials on how to use it are available as free downloads (Greenberg and Godin 2012; Greenberg 2013). The paragraphs below roughly follow the spreadsheet process, identify particular problems, and describe how they are mitigated by Timelapse.

Data Collection Requirements

The project biologist initially decides what data should be collected from the image sets and communicates those needs to the analysts. Though some data requirements are ubiquitous across projects, others are specialized to particular projects. In the spreadsheet method, the biologist specifies data requirements as column headers in a spreadsheet that analysts would then fill in. As such, the meaning of these headers, the data type, and the data format required were sometimes difficult for the analysts to understand or remember.

Timelapse mitigates these problems by providing the biologist with a specialized tool (Figure 4) to create a data template that specifies exactly what data should be collected for each image, how requests for those data should appear in the Timelapse user interface, and how data output should be labeled (Greenberg and Godin 2012). For example, in the first five rows of Figure 4, the biologist specified generic image information, including the date and time the image was taken, the image file and folder name, as well as the image quality. In subsequent



Id	Type	Default Value	Label	Data Label	Tooltip	Width	Copyable	Visible	List
1	File		File	file	The image file name	100	☐	☑	
2	Folder		Folder	folder	Name of the folder conta	100	☐	☑	
3	Date	DD/MM/YY	Date	date	Date the image was take	100	☐	☑	
4	Time	HH:MM:SS	Time	time	Time the image was take	100	☐	☑	
5	ImageQuality	Ok	Image quality	quality	System-determined imag	80	☐	☑	
6	Counter	0	Anglers (Shore)	anglers_shore	# anglers on shore	30	☐	☑	
7	Counter	0	Angerls (Ice)	anglers_ice	# anglers on ice	30	☐	☑	
8	Counter	0	Boats	boats	# boats with anglers in it	30	☐	☑	
9	Counter	0	Ice Tents	tents	# tents on ice	30	☐	☑	
10	Note		Lake ID	lake_id	ID of the water body	30	☑	☑	
11	Note		Analyst	analyst	Name of person analysin	50	☑	☑	
12	Note		Comments	comments	Add any comments here	90	☑	☑	
13	FixedChoice	0	% Visibility	visibility	Estimate of the % of the	50	☑	☑	0
14	FixedChoice	Open	Lake Condition	condition	Whether the lake is open	100	☑	☑	Open
15	FixedChoice	Unknown	Camera Type	camera	Type of remote camera u	50	☑	☑	

Figure 4. Data template tool, where the biologist creates all of the data fields of interest along with attributes that indicate how it will appear in the Timelapse user interface. This illustration shows a simpler subset of the data fields actually used by the authors.

rows, the biologist specified information tailored to the fisheries project, including what features of interest are counts (e.g., number of anglers [shore]), free-form notes (e.g., analyst name), and fixed choices that limit data values to a small input set (e.g., lake condition values are specified by a menu of possible values). Timelapse then reads in the data template to create a project-specific interface. Figure 5 illustrates this, where the data fields at its top were constructed from the data template in Figure 4.

TIMELAPSE eliminates this manual chore from the analyst's workflow by automating this first step, thus saving considerable time and reducing typing errors.

Analysts then fill in those fields on an image-by-image basis.

In our own practice at the Freshwaters Fisheries Society of BC, the data template proved invaluable as a way to structure data, where the template became the input standard applied to all image sets captured across many lakes and the output standard to facilitate uploading data to a provincial small lakes database.

The First Pass: Entering Routine Housekeeping Image Data

When analysts using the spreadsheet method receive an image set, they manually enter generic data describing each image: its folder and file name, the time and date that image was taken, and the image quality. This step is particularly time-consuming and tedious, especially when image names, times, and dates are out of order or missing.

Timelapse eliminates this manual chore from the analyst's workflow by automating this first step, thus saving considerable time and reducing typing errors. When Timelapse initially opens an image set, it extracts information from each image's metadata and uses that to populate its file and folder name and its time and date. It computationally determines the image quality as daytime, nighttime, or otherwise corrupt shot. These data are displayed in the Timelapse interface on the first row (Figure 5). If problems are found (e.g., because of ambiguities in how different cameras specify dates), Timelapse will query the analyst with ways of resolving it. We note that other image information may be available in the metadata (e.g., temperature and barometric pressure) and could be automatically extracted, although this is not done in the current software version.

Visually Searching and Inspecting Each Image

An analyst's primary task is to visually inspect each image for important features of interest. Though some features are determined by examining the image as a whole (e.g., lake conditions), other features require searching the image. When a camera captures a broad field of view, features of interest (such as a distant on-shore or ice angler, or a distant boat) may be quite small and difficult to spot (as evident in Figures 1–3). This is especially true if activities on that lake are rare and if lighting, fog, or shadows compromise image quality. Even when a feature is seen, the analyst must inspect it to classify what it is (e.g., an angler vs. a nonfishing person, a chair, or a shadow). We saw analysts using the spreadsheet method perform this search task by (a) repeatedly scanning the overall image, (b) magnifying details by zooming into the image, and (c) doing rapid image switching to spot differences in the scene across images. These

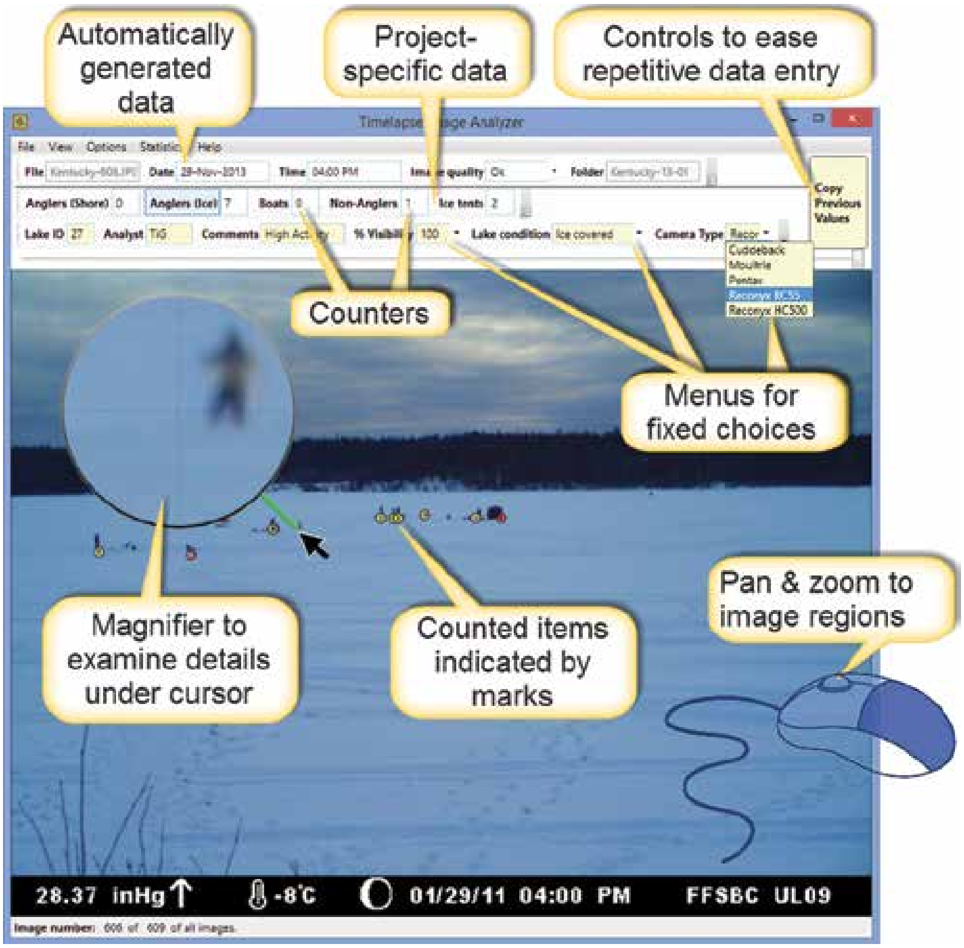


Figure 5. Annotated screenshot of the TIMELAPSE in action, displaying the image in Figure 3.

can be difficult or tedious with off-the-shelf photo viewers used in the spreadsheet method.

TIMELAPSE eases these search strategies. Magnification, which helps the analyst search for and identify features, is afforded by both a magnifying glass and a better pan/zoom interface. The magnifying glass (Figure 5, upper left) magnifies the area immediately around the moving cursor (the magnification factor is adjustable). For example, the analyst may search for anglers by running the magnifying glass over the shoreline or identifying small features on the spot by magnifying them. Alternately, the analyst can zoom into any region of the image using the mouse wheel and scroll around simply by dragging the image. Though the magnifying glass is faster, pan/zoom magnifies more of the scene. In all cases, magnification is fluid and performed in real time.

TIMELAPSE directly supports rapid image switching and integrates this with magnification. To explain, an angler will enter, move around, and leave a particular fishing location over time. This makes it unlikely that an angler will appear in exactly the same position across successive images. As mentioned, analysts had already exploited this in their search by rapidly switching between surrounding images, which makes even small appearances, movements, and disappearances of anglers pop out as an animation. Yet, the photo viewers used in the spreadsheet process reset the zoom level when switching between images, which meant that the analyst could only use image switching when fully zoomed out. TIMELAPSE remedies this by keeping the magnifying glass location and the pan/zoom settings constant during image switching. Thus, successive images are shown at exactly the same zoom level and centered on exactly the same location, where image features appear in exactly the same spot.

TIMELAPSE also offers image differencing as an alternative to image switching, where TIMELAPSE creates a composite image that highlights visual differences between the current and surrounding images (see Figure 6). Internally, TIMELAPSE compares pixels across images; if pixel values differ by a given threshold (to remove noise), that pixel is drawn in grey indicating the degree of difference; otherwise, it is drawn in black. Differences pop out as bright spots (Figure 6). Yet, because such spots can also be caused by uninteresting differences (e.g., moving shadows and objects shifting in the wind), the analyst must still inspect those spots by examining the unaltered image in the magnifying glass (Figure 6).

Entering Data

Analysts using the spreadsheet method had to enter data into the correct row matching the image and the correct column matching the data type. Though analysts tried to be vigilant, data entry proved error-prone: it was quite easy to mistype data and to misenter data into the wrong row or column. Thus, data entry had to be checked and rechecked. Analysts also reported problems tracking what was counted on images with many entities in it. Data entry in the spreadsheet method also proved tedious. Because analysts preferred keeping the image viewer maximized

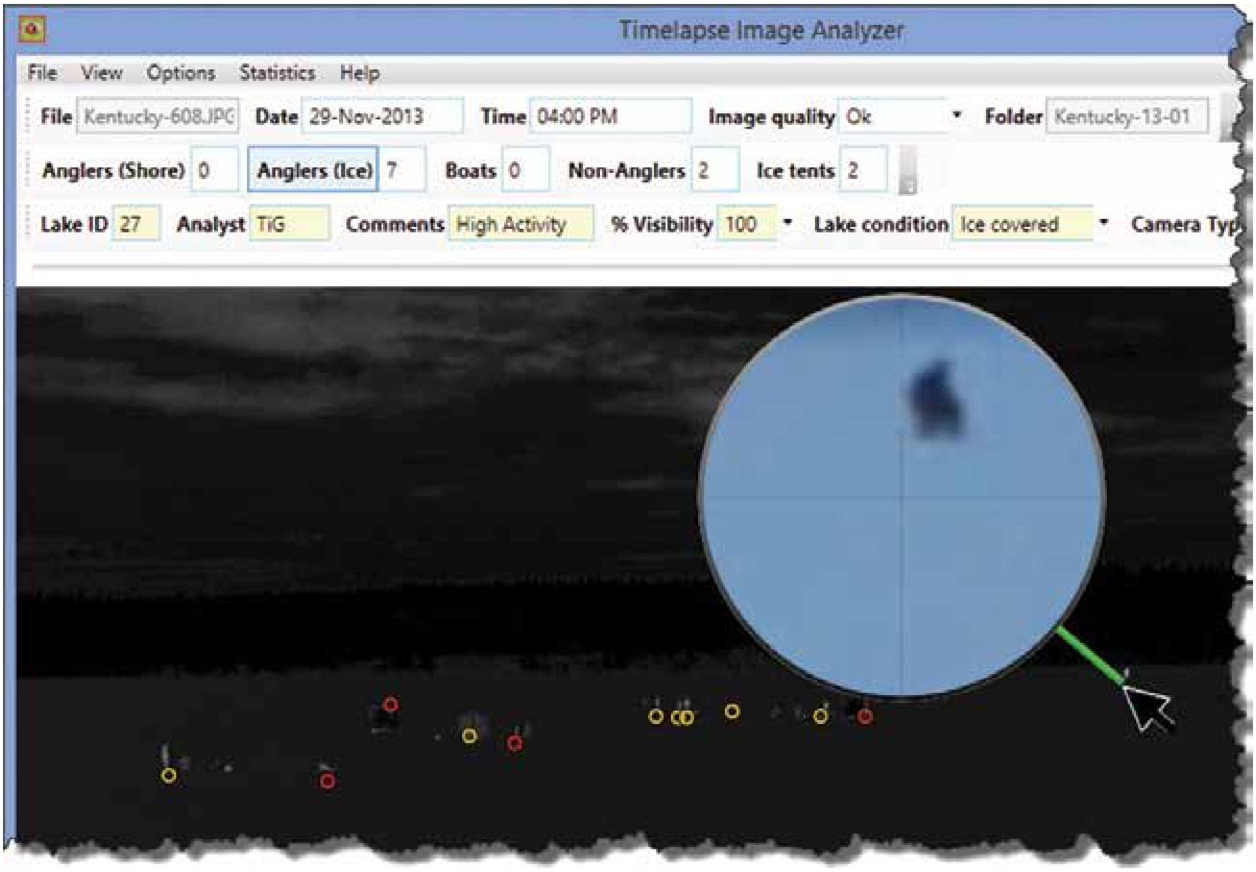


Figure 6. Timelapse image differencing feature, where the analyst is inspecting the enhanced grey spot next to the cursor (see Figure 5 for how this spot appears in the original image).

in order to see image details, they had to repeatedly switch back and forth between the viewer and the spreadsheet, sometimes as many as 30+ times per image. Additionally, data entry was quite repetitive when the information to be recorded changed little across multiple images.

Timelapse simplifies data entry. First, analysts fill in data fields on an image-by-image basis during image examination (Figure 5, top). This eliminates spreadsheet method errors resulting from data entered into the wrong spreadsheet row. It also eliminates window switching because its single interface combines both the image (Figure 5, bottom) and the data fields to be filled in (Figure 5, top).

Second, Timelapse minimizes typing, reducing both text entry errors and tedium. Only the data of the type "note" requires typing (e.g., lake id, analyst, and comments in Figure 5). In contrast, "fixed choice" data types provide a drop-down menu displaying a list of valid choices as specified by the biologist in the data template (e.g., the camera type menu in Figure 5 lists the known cameras). The "count" data type implements a special interface that simplifies and adds accountability to the counting process. To count a particular entity, the analyst selects the data field (e.g., anglers [shore], anglers [ice], etc., in Figure 5) and then clicks on those parts of the image where that entity appears. A small color-coded marker is drawn atop that location and increments the count in the corresponding data field. The analyst can also remove that marker to decrement the count. If the analyst hovers over that mark, its associated data field is highlighted and a description displayed: this allows double-checking. Markers are especially important for accountability and for minimizing errors on busy images because the marks make it easy to see what was or was not counted and to correct miscounts.

Third, Timelapse simplifies the entering of data that change little across multiple images (e.g., environmental changes over the course of a season, such as the "ice-covered" value for lake condition in Figure 5). The Copy Previous Values button (Figure 5, top right) applies to data fields marked copyable in the data template (Figure 4), where it copies data from the previous image to the currently viewed image. Each data field also has a context menu that allows the analyst to copy or propagate values across images in various ways, for example, across all images in the set or to back-fill empty fields from various points. Using these techniques, the specialist only needs to enter data when differences occur, rather than reenter the same data across all images in a sequence of similar images.

Finally, analyzers wanted to deal with particular types of images in bulk, such as nighttime shots. Timelapse provides image filters that show only the subset of images matching a particular attribute. One filter, for example, displays only very dark images (specified as dark in the image quality field; see Figure 5). Using that filter, the analyst can quickly scan them to verify that they are nighttime shots (which comprise over one-third of all images currently collected in BC) and then propagate a single field across all of those images to mark them, for example, "% visibility = 0." Another filter captures corrupted images, which can be dealt with in a similar manner. A third filter shows only nondark and noncorrupted images, which will be the primary focus of the analysis. With these filters, the specialist can quickly deal with unimportant images.

Correcting Common Errors

Our analysis revealed several sources of errors that are painful to correct. One example is date and time errors caused by mistakes in initial camera setup or introduced due to changes between daylight savings and standard time. When this occurred in the spreadsheet method, analyzers had to change the data and time fields manually across almost all images. To relieve this burden, Timelapse allows the analyst to bulk correct these errors (using dialog boxes) by adding a correction value to all dates (which handles incorrectly initialized cameras), changing the time from a certain point onwards (which handles daylight saving/standard time issues), or specifying a starting time that propagates by set intervals across all images (useful when dates and times were not recorded in the image metadata).

Validating Data

After the analysts complete their task, the data need to be checked and validated. Beyond data accuracy, validation also allowed the biologist to gauge the abilities of the analyst. This was difficult to do in the spreadsheet method due to the separation of the spreadsheet data from the source images and because it was unclear what the analyst had actually counted on each image. Timelapse eases validation, where the biologist can efficiently spot check or thoroughly validate the data collected against each image. The biologist can quickly navigate through images and its associated data to see what was counted and to scan for anomalies. Corrections can be done on the spot. The biologist can review the markers to check what entities were counted and how they were identified and review the image to see whether any entities were missed (Figure 5).

Time Savings

Timelapse has been in active use for almost four years as an assessment tool for small lakes fisheries in BC. Technicians and biologists have used it to obtain angler counts from over a million images from quite different lake types and from different regions of the province. Compared to the original image analysis method, the improvements afforded by Timelapse have been dramatic, as estimated by two methods.

First, we retrospectively examined our analysts' hourly payment records to calculate cost differences against the method used to analyze those images. We compared each analyst's average time to do various image sets using the original spreadsheet method versus Timelapse. Our calculation is only an estimate: image sets differed, and we know that the overall total time charged to analyze an image set sometimes included secondary activities. Even so, we saw a marked decrease in cost, typically ranging 30%–60% (depending on the individual analyst), to analyze image sets with Timelapse versus the original spreadsheet method.

Second, we designed a somewhat more "controlled" scenario to compare analysts' efforts when using Timelapse versus the spreadsheet method. We assembled six image sets: two culled from an urban fishery study site, two from a medium-effort winter fishery, and two from a high-effort winter fishery. We also assembled two other image sets to be used for training purposes. We gave these image sets to six analysts. For each study site, we asked the analyst to encode one image set using the spreadsheet method and the other image set using Timelapse. To account for learning effects, all initially practiced the analysis method with a training set. We asked them to track the actual hours spent encoding each image set and to provide comments about particular details of how they went about it.

Our results show wide variability between analysts for the time taken to encode images, regardless of the study site or the analysis method (Table 1). Differences between analysts contributed to this variability, including their speed, their experience, and the strategies they used for analyzing images (e.g., some analysts would review an image several times in an effort to be thorough, whereas others would not). Differences in the hardware used also contributed to variability, such as the size and number of screens used to display images.

More important, our data revealed that, in each and every case, all analysts processed considerably more images per hour using Timelapse when compared to the spreadsheet method for all site types. We performed a two-factor analysis of variance (study site type [3] × analysis method [2]) of images processed per hour (see Table 1 for summary data). The analysis revealed a significant interaction effect of study site type × analysis method ($F_{2,10} = 10.809$, $P = 0.003$). Unsurprisingly, the study site type affected the degree of difference because different sites produce images of different complexity and fidelity. Yet, the analysis method alone also proved significant ($F_{1,5} = 39.600$, $P = 0.001$) where every analyst processed images from the same study site considerably faster using Timelapse versus the spreadsheet method. These differences are also practically significant. The percentage difference in speed (Table 1, last column) equates to the percentage improvement in the images per hour processed by an analyst using Timelapse versus the spreadsheet method, where the improvement ranges between 173% and 244%.

In summary, we saw that Timelapse versus spreadsheet method analysis introduced a cost savings in our payroll ranging from 30% to 60% and an improvement in speed in our image analysis study ranging from 173% to 244%. Thus, it is reasonable to conclude that image analysis using Timelapse is generally two times more efficient (twice as fast or half the cost) when compared to spreadsheet analysis (see final two rows in Table 1, which collapses the images/hour across all study site types).

DISCUSSION

Fisheries professionals have been promoting adaptive management experiments that are applied at a regional scale (Lester et al. 2003; Parkinson et al. 2004; Hunt et al. 2011). As previously discussed, aerial surveys and creel surveys by themselves may not be feasible or appropriate, for example, due to cost and/or precision issues (Parkinson et al. 1988; Tredger 1992; Parker et al. 2006). This has led to the use of remote cameras as a third intermediate method of collecting angler counts for multiple waterbodies (cheaper than creel) with a better temporal resolution than aerial surveys. In conjunction with instantaneous counts, angler counts taken from these images can be used to calculate good effort estimates (van Poorten et al., pers. comm.). These counts and effort estimates can be used on their own or can complement other estimates of effort in larger-scale studies (Parnell et al. 2010; Smallwood et al. 2012). For example, in Australia, cameras were incorporated into aerial-roving surveys to provide a more cost-effective method of measuring shore-based fishing across a 24-hour day (Smallwood et al. 2012). British Columbia's use of camera-based angler counts provides several other examples. As mentioned, BC biologists calculated effort estimates in conjunction with instantaneous counts (or creel survey data). However, if those data were unavailable, or if cameras were set up to only capture hotspots, access points, or a small portion of a large lake, BC biologists could still use camera count data as an index of fishing effort trends over time.

Table 1. Average number of images per hour analyzed by analysts, categorized by the study site type and the analysis method. The final column indicates differences in speed as a percentage when using Timelapse to analyze particular study sites versus the spreadsheet method. NA = Not applicable.

Study site type	Analysis method	Images per hour	Standard deviation	% Difference in speed
High winter	Timelapse	488.5	76.8	244.0
NA	Spreadsheet	200.0	78.9	NA
Medium winter	Timelapse	221.0	69.9	181.0
NA	Spreadsheet	122.8	43.3	NA
Urban	Timelapse	353.3	147.0	173.0
NA	Spreadsheet	203.1	44.0	NA
All sites	Timelapse	354.5	148.8	200.0
NA	Spreadsheet	175.3	66.6	NA

In those circumstances, indices of effort are somewhat similar to those obtained by aerial surveys but are preferable in that daily and seasonal temporal trends are obtainable.

Of course, new fishing management methods must be considered carefully in terms of costs versus benefits, especially in the context of limited agency resources. Though cameras have clear benefits, they incur costs, such as camera purchases, technician salary for retrieving images, the cost of acquiring the instantaneous counts to calibrate camera counts to real effort, etc. Of these, the visual analysis of the thousands of images captured by these cameras proved expensive. Timelapse mitigates this expense, where its design supports the best practices technicians use to analyze images. Compared to the original image analysis method, technicians are about twice as fast at analyzing images, resulting in a marked cost savings. Estimates of actual overall cost savings can be easily predicted by agencies. As an example, consider an agency in the province with the following parameters. The cameras deployed by the agency are configured to capture one image every hour, for a total of 8,760 images per camera per year. Technicians are paid $20/hour. Using the images/hour rates (Table 1, last two rows), the analyst cost to analyze each camera's images would be about 50 hours ($1,000) using the spreadsheet method but only about 25 hours ($500) using Timelapse. If the agency had 86 cameras deployed, the total yearly cost would be reduced from $86,000 using the spreadsheet method to $43,000 using Timelapse.

Timelapse offers other advantages. First, because the quality of data returned is standardized, formatting errors are almost eliminated and corrections (if any) are fast to do. As a result, data can be uploaded directly into provincial databases and/or used almost immediately for estimating angling effort. Second, the ability to validate the angler counts (to see exactly what analysts counted in each image) saves biologists time when double-checking data. Third, the ease of validation provided by Timelapse can help biologists train technicians. For example, the biologist can provide a technician-in-training with a small image set and then easily review any counting errors made. Finally, Timelapse has been well received by technicians. Though image analysis is still labor intensive, they feel that they are working efficiently.

Though our own interests lie in small lakes, strategies such as those found in Timelapse can be exploited in a broader range of projects employing remote cameras, including resource use across rivers, marinas, and passages; access ramp activity; parks use; facilities use; fishing demographics; boat traffic; and counting other human activities in the area. Indeed, Timelapse use already goes beyond fishing; it is currently being used by wildlife biologists to track wildlife and human use in national parks and other sensitive areas, where millions of images have already been analyzed. In BC regional parks, Timelapse has been used to analyze trailhead images to collect data on parks use (hiking vs. biking vs. angling) and demographics (male vs. female vs. child; Iain Lunn, BC Ministry of Forests, Lands, and Natural Resource Operations, personal communication). We are also in the early stages of exploring its use for counting salmon and salmon redds in high-resolution images of streams.

AVAILABILITY

Timelapse software, installation instructions, tutorial documentation (including example image and data template files), and mailing list information are freely available at saul.cpsc.ucalgary.ca/timelapse. Documented source code is included, where software developers can modify or enhance its behavior if needed.

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