

Using mobile technology to track wine tourists

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ABSTRACT

Understanding how tourists behave when visiting a destination is invaluable information for businesses. Despite the prevalence of wine tourism and its economic contribution, prior research has typically used surveys which produce coarse data. In this study, we used an innovative mobile phone app with integrated survey and Global Navigation Satellite System (GNSS) technology to examine the movements of wine tourists within an Australian wine region. This method offers a finer grained spatio-temporal approach for understanding wine tourist behaviour and has implications for the marketing and planning that occurs within wine regions.

1. Introduction

Wine tourism is a growing phenomenon within several destinations throughout the world, particularly in New World wine countries such as the USA, New Zealand, and Australia. Old World wine countries such as France and Spain continue to attract significant numbers of wine tourists due to their traditional charm and history. According to seminal researchers Hall, Sharples, Cambourne and Macdonald (2000, p. 3), wine tourism can be defined as “visitation to vineyards, wineries, wine festivals and wine shows for which grape wine tasting and/or experiencing the attributes of a grape wine region are the prime motivating factors for visitors”. In Australia alone there are nearly 1600 cellar doors, spread throughout the country’s 65 geographically classified wine regions (The Australian and New Zealand Wine Industry Directory, 2019). The combined expenditure of domestic and international wine tourists visiting Australia is approximately \$7.1 billion USD annually. In the United States, wine tourism generates around \$20 billion USD in revenue (Mintel, 2017); while 27% of all holiday visitors to New Zealand visit a winery and overall, spend just over \$2.7 billion USD per year (New Zealand Winegrowers Inc, 2018).

On a global scale, the wine industry comprises thousands of distinct geographic regions that are often marketed collectively according to the unique strengths of their climate, location, and attractions. Collaboration at an industry (or destination) level can enable wine producers to

more productively use and spread information (Anderson, 2001), maintain industry standards, lobby governments, invest in research and development, create new products, and gain entry into national and international markets (Cox & Wray, 2011; Lindgreen, 2001, 2008). Previous research has also found that horizontal networks and collaborative marketing can provide significant benefit to the individual firm, particularly those in premium wine regions (Lewis, Byrom, & Grimmer, 2015), and is key to the design of successful wine routes (Sigala, 2019a, 2019b).

At a national level, Australia has invested significantly in projects designed to diversify the wine tourism offering and enhance visitor satisfaction and enjoyment. Despite the growth of wine tourism, many individual wineries and destinations lack the individual resources to collect reliable and accurate information on their cellar door visitors. This creates issues in terms of their ability to make ‘smart’ management and marketing decisions, such as what services and activities they should offer and when, who they should collaborate with in terms of other wineries or tourism operators, or which consumer segments they should target. If information is collected, it is normally not shared at a destination or regional level, leading to decisions made in isolation. Advancements in Information and Communications Technology (ICT) and Global Navigation Satellite System (GNSS) tracking have led to the development of ‘big’ data sets that can determine in high resolution, how tourists move between winery cellar doors, in both space and time.

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As a tool for studying tourist behaviour, a distinct advantage of GNSS device tracking is that it provides data that is both global and spatio-temporally accurate (Li, Xu, Tang, Wang, & Li, 2018). When this type of data is collected on a large-scale, destination management organisations (DMOs) can better understand travel decisions and manage visitor behaviour (Reinhold, Laesser, & Beritelli, 2018). Through the application and integration of ICT, DMOs can also offer tailored and aggregated tourist experiences, gather and distribute information in a more intelligent and collaborative manner, and therefore enhance their competitiveness (Buhalis & Amaranggana, 2013; Gretzel, Sigala, Xiang, & Koo, 2015).

Although knowledge of tourist behaviour obtained via tracking methods is expanding, no prior studies have applied this methodology to study the precise travel patterns of visitors to winery cellar doors. To date, most studies have used traditional data collection methods such as surveys, where 'wine tourists' are asked to self-report their experiences and motivations either in field, or at the end of their holiday. As such, a gap in the literature exists to understand the application and benefits of ICT to wine tourism research, and specifically the role of data obtained via GNSS tracking as a mechanism for collaborative marketing, and smarter management of the experiences available to tourists within a region.

In this paper, we present the results of a study conducted as part of a broader research program. Using tracking and survey data collected in 2016, 2017 and 2018, we investigated the precise travel patterns, itineraries, and demographics of wine tourists in one of Australia's most premium wine regions. A further aim of our study was to pilot a new method for wine tourism research, given the limitations associated with self-reporting and self-administered surveys. The next section will discuss recent advancements in the field of wine tourism, followed by a summary of developments in the field of tracking tourists.

2. Wine tourism and cellar door visitors

An established body of literature surrounds the concept of wine tourism. Previous researchers have identified and discussed a range of topics, including who wine tourists are (Charters & Ali-Knight, 2002; Nella & Christou, 2014; Pratt, 2014, 2019), their attitudes and behaviours (Bufquin, Back, Park, & Nutta, 2018; Galloway, Mitchell, Getz, Crouch, & Ong, 2008; Yuan, Morrison, Cai, & Linton, 2008), and their motivation to visit cellar doors and their intentions to visit (e.g. Back, Bufquin, & Park, 2018; Park, Bufquin, & Back, 2019; Sparks, 2007; Yuan et al., 2008). Other work has examined what factors determine the brand value of, and consumer demand for, certain wine tourism destinations (Getz & Brown, 2006; Gómez, González-Díaz, & Molina, 2015), the structural dimensions of wine routes (Bruwer, 2003), producer perceptions of wine tourism (Alonso & Liu, 2010), the relationship between rural cultural systems and the production and consumption of wine tourism (Mitchell, Charters, & Albrecht, 2012) and the use of websites and social media to attract wine tourists (Alonso, Bressan, O'Shea, & Krajsic, 2013).

Over the past two decades several researchers have studied the motivations, attitudes and behaviour of wine tourists and segmented them according to their level of wine interest and knowledge. Charters and Ali-Knight (2002), for example, surveyed 368 wine tourists and classified them according to their wine knowledge and involvement, motivation to visit wineries, and expectations and perceptions of wine education. Their study resulted in a widely adopted framework, which categorises wine tourists on the basis of their interest in wine and motivation for visiting a winery. Similarly, Galloway et al. (2008) segmented wine tourists into two groups according to whether their sensation seeking behaviour was high or low. Not surprisingly they found that higher sensation seeking wine tourists engaged in more visits to wineries, participated in more activities during a visit to a wine region, were more likely to venture 'off track', and were more likely to use the internet as a source of information about wineries Galloway et al.

(2008). In addition, (Assero & Patti, 2011) found similar results to other studies regarding the motivations and behaviour patterns of wine tourists. Using self-administered questionnaires with cellar door visitors (which they collected upon entry to the cellar door and returned upon exit) the authors confirmed that the factors influencing wine tourist visits to cellar door include both the winery and wine region's reputation, and whether the tourist has an interest in wine.

Other researchers have moved beyond segmentation studies and focussed more on the spatial movement and behaviour of wine tourists. Alant and Bruwer (2010), for example, compared the intra-region visitation patterns of wine tourists across two well-known and branded wine regions in order to generate specific winery visitation sets. They used a traditional method of in-person questionnaire interviews with a random sample of visitors across 25 winery cellar doors, to explore how wine tourist behaviour was shaped by the region, the winery and whether the tourist was a first time or repeat visitor. Overall, the study found that the mean number of cellar door visits was 4.8 per day, however this was influenced according to how accessible the cellar doors were to a main highway, and the length of time the tourist was spending in the region.

More recently, Popp and McCole (2016), sought to understand wine tourists' itineraries and movements in an emerging wine region using a paper-based itinerary mapping method, as GNSS technology was considered too expensive and challenging. Their technique of itinerary mapping involved "providing visitors with a paper map of an area and asking them to indicate their movements within the study region on the map, indicating travelling routes and stops." (Popp & McCole, 2016, p. 992). While this approach elicited significant findings regarding behaviour, participants' precise spatio-temporal movements were not recorded. The study was also limited as respondents were recruited once they were at a winery cellar door, as opposed to recruiting tourists as they enter a destination or state and being able to track their movement before arriving in a wine region and/or cellar door.

Traditional wine tourism studies that recruit participants when they are at a cellar door or winery elicits data on mobility *after* they have visited the particular cellar door, not before, thus it is limited. To date it appears that a significant dearth exists within the wine tourism literature in relation to capturing real-time data that more accurately captures how exactly tourists move between cellar doors, precisely how long they spend at them, and what 'other' attractions they visit during their stay.

3. Tracking tourists

Recent advancements in technology have contributed to a rise in the use of tracking technology to research how tourists reach and/or move within certain destinations and there is now a vast array of options for researchers to understand how tourists move through time and space (Hardy, 2020; Shoval & Isaacson, 2010). Methods include Bluetooth and Wi-Fi tracking that identify phones when they pass by either their Bluetooth or Wi-Fi receivers. Researchers may also choose to use location data that can be obtained from mobile phone companies (for example, see the work of Raun, Ahas, & Tiru, 2016; and Ahas, Aasa, Mark, & Pae, 2007; Ahas, Aasa, Roose, Mark, & Silm, 2008; Ahas, Silm, Järv, Saluveer, & Tiru, 2010). However, while these techniques produce vast amounts of data and can be cost effective (Versichele et al., 2014), they are limited in their ability to determine who the tourists are, and importantly, are unable to generate data regarding the socio-demographic or psychographic profiles of the tourists. Moreover, both Wi-Fi, Bluetooth and the use of mobile phone data are subjected to privacy concerns (Oosterlinck, Benoit, Baecke, & Van de Weghe, 2017). While the data is disaggregated, contention remains over the ability to re-identify users based on media access control addresses or their unique identifiers.

The online digital traces of tourists offer a further technique through which the movement of tourists may be understood. Social media users, for example, can now disclose their location using geotags, which record the location coordinates of images, videos, or texts taken by

smartphones and some digital cameras. This has led popular social media platforms such as Facebook, Twitter, and Instagram to integrate geotagging into their core functionality. As Wilken (2014) has argued, geotags can be extremely useful marketing data because it facilitates an understanding of where tourists travel. However, the practice of scraping this data en-masse has been prohibited by Facebook, and therefore Instagram, due to privacy issues. While platforms such as Flickr and Twitter still allow for automated data scraping, there are troubling implications for user privacy and consent (Hardy et al., 2017).

To counteract concerns regarding privacy in the context of smart tourism (Gretzel et al., 2015), GNSS enabled devices (such as watches or loggers) have been used for tourist tracking resulting in highly accurate results (Yun & Park, 2015). Studies regularly combine GNSS tracking with other methods, such as paper-based surveys, to assess different types of tourists' movement. Hikers have been studied in South Carolina (Beeco & Hallo, 2014; Hallo et al., 2012); visitors to Virginia have been tracked (Beeco et al., 2013); tourists in Hong Kong, Melbourne and Sydney have been explored (Edwards & Griffin, 2013; Grinberger, Shoval, & McKercher, 2014; McKercher, Shoval, Ng, & Birenboim, 2012; Shoval, McKercher, Ng, & Birenboim, 2011); as well those in theme parks (Birenboim, Anton-Clavé, Russo, & Shoval, 2013); those attending sports events (Pettersson & Zillinger, 2011); tourists in German cities (Modsching, Kramer, Hagen, & Gretzel, 2008); and cruise ship tourists (De Cantis, Ferrante, Kahani, & Shoval, 2016). However, this form of research is limited to brief temporal periods; GNSS battery life is notoriously short, and most studies have only been able to track tourists for one day (Edwards & Griffin, 2013; Grinberger et al., 2014; McKercher et al., 2012).

Faced with these limitations, the research team responsible for collecting data for the current study was required to design an app that a) complied with the Australia National Statement on Ethical Conduct in Human Research (2007) - the jurisdiction where the research was being conducted; b) would collect fine grained detail on movement while not draining a mobile phone's battery life; and c) could track tourists for long periods of time and over entire destinations or geographical areas. The result was an app called Tourism Tracer (Hardy et al., 2017). The app was designed to track the movement of tourists to within 10 m of accuracy, every 1–2 s. It also contained a survey which was synced with the GNSS data, allowing for insights on how different types of tourists travelled. The technology resulted in highly detailed information on how tourists travelled through entire destinations for the duration of their stay (Hardy et al., 2017), and insights such as the factors that influenced dispersal (Hardy, Birenboim, & Wells, 2020). It also challenged current understandings of special interest tourists (McKercher, Hardy, & Aryal, 2019) and resulted in a machine learning program that could predict tourist behaviour (Hardy & Aryal, 2020).

4. Methodology

4.1. Data collection

The main purpose of this study was to track international and domestic out-of-state tourists' movements within a premium wine region, so to further understand (and predict) cellar door visitor behaviour. To address this aim, the research team used data collected from the larger Tourism Tracer study, described above. In the Tourism Tracer study, after participants were recruited and consented to take part in the study, they were invited to fill in an entry survey in the app, which provided information on their travel motivations, socio-demographic status, travel party size and previous visitation to Tasmania. The survey data synced with GNSS data, which was recorded every 1–2 s, with 10 m of accuracy. The methodological approach and the decision behind the choice of technology, including its constraints and limitations, have been discussed in detail in Hardy et al. (2017).

The Tourism Tracer research team collected tracking and survey data using two methods. For the first 20 months of the study (i.e. February

2016 to November 2017) the app was installed on a study phone that was handed out by recruiters; a total of 934 tourists were recruited during this phase. Participants were recruited via convenience sampling at one of the three gateways into Tasmania: Hobart Airport, Launceston Airport or Devonport Seaport where they approached as they passed the recruitment station, if a recruiter was free. They were incentivised for their participation with three gigabytes of data being placed on the study phones, which could be used via their own devices through 'hot spotting'. They were also given a digitised map of their travel route upon the completion of their holiday.

In late 2017, a stand-alone app was made available to download onto participants' personal mobile phones and was advertised via signs but without active recruitment at the three entry ports leading to the self-selected recruitment of a further 168 tourists in the first half of 2018. Analysis of survey responses showed that these tourists were demographically indistinct from the tourists recruited in-person in terms of their place of residence, gender, age, reason for visiting Tasmania, and income. Furthermore, because the two methods of data collection used the same app, had the same output format, and took place over a short period of time, both data sets have been used in this study. Following both tranches of data collection, the data was cleaned using an algorithm based on estimated position error, speed, and nearness to other points to remove erroneous points, and then analysed using the statistics package 'R' (R Core Team, 2021) as well as ArcMap (ESRI, 2011).

4.2. Study context and area

In order to explore the precise spatio-temporal movements of wine tourists, the research team opted to use the Tourism Tracer data set, outlined above. We focused on a single wine region in Tasmania (the Tamar Valley), which compared to others in the state, has the greatest number of cellar doors in relatively close proximity to each other along a defined touring route. The region also has its own destination marketing organisation or member-owned network that publishes a region-specific brochure and website. Most Tamar Valley cellar doors are also featured in the state-wide wine trail brochure. At the time of our study, this relatively large sub-region comprised 31 cellar doors and 24 attractions that we deemed to be other points of interest for tourists.

From an industry perspective, as Australia's southern-most and only island state, Tasmania is ideally located to produce high quality, cool-climate wines. The state comprises 160 licenced wine producers, who together harvested 17,180 t of grapes in the 2018/19 season (or approximately 1.24 million cases of wine). Although Tasmania only produces 1% of Australia's total wine output, the state accounts for just over 4% of Australia's total wine value and is reported to be the 8th most valuable wine region in the country (Wine Tasmania, 2020).

4.3. Data analysis

As mentioned previously, data for this study were collected as part of a larger study that investigated the movement of free and independent travellers in Tasmania, Australia. In order to analyse the data related to wine tourist movements, the first analytical step was to create a GIS polygon shape file of the Tamar Valley region. This was then defined as the area east of the western West Tamar Council border. A discretionary border was used for the eastern boundary that excluded the town of Scottsdale but included the northern coast. The GNSS coordinates of Wine Tasmania members who operated a cellar door within the polygon were then included. The GNSS coordinates of associated tourist attractions were also identified manually, using street maps overlaid with the GNSS data.

The next step in the analysis process focussed on determining the number of tourists (or study participants) who had visited the Tamar Valley. This required an assessment of the duration and frequency of points that were captured for each tracked device in the Tamar Valley area. If a tracked device was only within the Tamar Valley on one day

and captured less than five GNSS points, the GNSS track was examined and, in most cases, the data was excluded (as it was considered to be too minimal to constitute a visit). This process of examining the duration and frequency of tracked devices resulted in 473 tourists being identified as travelling through the Tamar Valley during both tranches of data collection.

In order to determine which tourists visited a winery cellar door, GNSS points with a speed of less than fifteen kilometres per hour that were within the borders of each Tamar Valley cellar door were used to classify a visit. This step resulted in 86 Tamar Valley wine tourists being identified. Using the 'R' with the dplyr package (Wickham, François, Henry, & Müller, 2019) and the date and time for each visit, an itinerary was then created for each tracked device. Following this, the socio-demographic characteristics of the wine tourists ($n = 86$), Tamar Valley tourists ($n = 473$), and general Tasmania tourists ($n = 1038$) were identified using survey data collected via the study phones or mobile phone app.

5. Results

5.1. Sample profile

In profiling our sample, the research team assessed the socio-demographic data pertaining to the Tamar Valley wine tourists and compared this with the other main data sets: i.e. Tamar Valley tourists and Tasmanian tourists. First, the descriptive statistics were observed (see Table 1).

From the descriptive statistics, factors were chosen to use in a binomial logistic regression model to determine socio-demographic factors related to tourists' decision to visit the Tamar Valley if they did not visit a cellar door there, and which factors determine that Tamar Valley tourists will visit a cellar door. The models were created in R using the generalised linear model tool and tested with different combinations of factors with the best fit analysed through consideration of the Akaike information criterion and plots of the residuals. While some factors were not found to be significant on their own, they were used in the models if they contributed to the goodness of fit, or if they were significant in one model, but not the other. Income level was collected as an ordinal categorical variable with income brackets in the Tourism Tracer survey. Income level was included as a metric variable in the regression with equidistant scores assigned. Data concerning entering and leaving the state was combined so that whether a gateway was used at all was included as a binary variable. As some tourists chose not to complete every survey answer, three were dropped from analysis due to missing data.

Analysis of the logistic regression results (Table 2) shows that factors that were associated to Tasmanian tourists visiting the Tamar Valley are private transport in the form of a car, either their own or a rented one, using Launceston Airport to enter and/or exit the state, and having a long length of stay. An interest in food and wine also had a positive association. Being a repeat visitor to Tasmania, a domestic tourist, and using Hobart Airport were also factors inversely related to visiting the Tamar Valley.

From the Tamar Valley dataset, the factors which were associated to tourists visiting a least one cellar door were a stated interest in food and wine, a higher income level and the tourists using Launceston Airport as an entry or exit point.

5.2. Cellar door visits and movement behaviour

In terms of their movement behaviour, the Tamar Valley wine tourists were found to have made 157 stops between them at 22 different cellar doors. The cellar door with the highest visitation rate recorded 27 tracked devices (wine tourists). Nine wineries did not record any tracked devices. It is worth noting that at the time of the study these nine cellar doors were either not open to the public at regular times, or where

Table 1

Descriptive statistics of all study participants, all tourists who visited the Tamar Valley, and Tamar Valley wine tourists.

	All participants (tourists) in the Tasmanian study	General Tamar Valley tourists	Tamar Valley wine tourists
Total number ^a	1038	473	86
Average age (in years)	46.0	47.2	48.0
<i>Country of origin</i>			
Australia	71%	70%	81%
Mainland China	3%	2%	2%
Hong Kong	4%	4%	5%
Other overseas country	22%	23%	12%
<i>Number of travelling companions</i>			
Travelling alone	9%	7%	4%
A couple	53%	54%	59%
A group of three	11%	10%	7%
A group of four	12%	15%	14%
A group of five or more	14%	14%	16%
<i>Household income (per annum)</i>			
0–\$52,000	22%	22%	16%
\$52,000–\$104,000	29%	31%	23%
\$104,000–\$150,000	15%	13%	14%
\$150,000–\$200,000	8%	10%	17%
Over \$200,000	15%	13%	17%
<i>Repeat visitor to Tasmania?</i>			
Yes	50%	46%	53%
No	50%	54%	46%
<i>Port of entry</i>			
Hobart Airport	61%	44%	49%
Devonport Seaport	29%	38%	28%
Launceston Airport	9%	17%	23%
<i>Port of exit</i>			
Hobart Airport	52%	34%	36%
Devonport Seaport	26%	36%	27%
Launceston Airport	12%	20%	30%
<i>Reason for visit</i>			
To see wilderness/ wildlife/natural scenery	49%	53%	46%
To experience Tasmanian food/ wine	8%	9%	19%
To visit Tasmanian friends or relatives	14%	13%	8%
To experience Tasmania's history/heritage	11%	12%	11%
To experience Tasmania's art and culture	5%	3%	5%
Some other reason	12%	8%	11%

^a Less than the total number of participants in the larger study, as some tourists did not complete the entry survey from which these variables are sourced. Some variables also do not add up to 100% as some participants skipped questions.

located a far distance from major arterial roads or touring routes. A further six cellar doors attracted between 10 and 20 tourists, while nine cellar doors only had one or two participants visit their cellar door during the Tourism Tracer data collection periods.

Our study also used GNSS tracking data to determine the average time spent in cellar doors, by subtracting the date-time of the first point inside the border from the last for each tracked device. A small amount of tracked devices only had one or two points inside a cellar door. They were removed from the time spent calculation as the time stamped data was not definitive but were still considered to have visited the location due to the speed and location of their GNSS data.

Table 2

Binary logistic regression models of the factors affecting visitation to 1) the Tamar Valley and 2) a cellar door in the Tamar Valley region.

	From total dataset: Visited Tamar Valley but did not visit a Tamar CD	From Tamar Valley dataset: Visited a CD
Age	0.007 (0.005)	−0.0002 (0.010)
Travelling as a couple	−0.238 (0.158)	0.120 (0.261)
Income level	0.025 (0.050)	0.190* (0.084)
Has a car: rented or owned	1.362*** (0.350)	0.520 (1.071)
Visited Tasmania previously	− 0.792*** (0.190)	0.321 (0.305)
Interest: food/wine	0.625* (0.307)	1.195** (0.377)
Entry/exit from Hobart airport	− 1.322*** (0.180)	0.550 (0.286)
Entry/exit from Launceston airport	1.669*** (0.224)	0.715* (0.288)
Domestic Tourist	− 0.573** (0.198)	0.527 (0.357)
Number of days in state	0.167*** (0.020)	0.042 (0.033)
Intercept	−1.876*** (0.474)	−4.388*** (1.229)
Observations	952	470
Log Likelihood	−500.682	−199.025
Akaike Inf. Crit.	1023.363	420.050

Note: * $p < .05$; ** $p < .01$; *** $p < .001$

As shown in Table 3, the time spent in cellar doors was often quite short and varied widely from minutes to a couple of hours. The effects of offering extra attractions and facilities, such as restaurants and tours, as well as having a convenient location on a major arterial road were theorised to increase visitation numbers and duration. To test this hypothesis, we first grouped the cellar doors according to their location and if they offered other attractions. Because this data was not captured in the larger Tourism Tracer study, secondary data from the local and state-wide wine route brochures (published around the time of the study) was used for this purpose. Mann-Whitney tests were then conducted using the duration of each cellar door visit. Comparing the time spent in cellar doors on and off major arterial roads revealed no significant difference ($Mdn_{off} = 10$ m, $Mdn_{on} = 19$ m, $U = 1739.5$, $p = .22$), however, the time spent in cellar doors offering other attractions was significantly longer than in cellar doors without other attractions ($Mdn_{noOA} = 3.5$ m, $Mdn_{OA} = 18.2$ m, $U = 2494.5$, $p < .001$).

Comparing the number of visits to each cellar door with a Pearson's chi-square goodness-of-fit test generated similar results. Major roads did not have a significant effect on the number of visitors ($X^2(1) = 0.30$ $p = .58$), however, offering 'other attractions' did significantly increase the visitor average ($X^2(1) = 9.89$ $p = .002$) (Table 4). While these results are in line with extant literature, which suggests additional attractions can be an effective method of enticing tourists to a cellar door (e.g. Lewis & Lehman, 2020) and adding to the complete winery experience (Alant & Bruwer, 2010), it should also be noted that for the purposes of this study we did not measure the type of 'other attraction', nor did we measure the reputation of each cellar door, which arguably may also be influencing

wine tourist behaviour.

Due to the low effect 'location on a major arterial road' appeared to have on visitation, we examined whether different location attributes were more impactful. Using general movement data we collected in the Tamar Valley, we examined whether the cellar doors were inconveniently far from general tourist flow, and whether location on a popular tourist route (or sub-region) enhanced the number of visitors. These sub-regions (see Fig. 1) were classified as East of kanamaluka / River Tamar, West of kanamaluka / River Tamar, and South of kanamaluka / River Tamar.

A 5 km search radius was employed around each cellar door, and each unique tourist track was counted. The results have been plotted in in Fig. 2. The number of tourists within 5 km of each cellar door had a distinct spatial correlation, as there were three clusters of highly similar tourist numbers that correlated to the geographical location of the cellar doors. In the East sub-region, there were between 67 and 89 tourists within 5 km of all cellar doors. In the West sub-region, there were between 164 and 182 tourists within 5 km of all cellar doors. And finally, in the South sub-region there were 376 and 384 tourists within 5 km of all cellar doors. A single factor ANOVA test confirmed that this variance was statistically significant ($F(2,19) = 1553.6$, $p < .0001$). A similar analysis of the variance between visit numbers in each sub-region did not find a distinct difference ($F(2,19) = 1.12$, $p = .34$).

The inability for nearby tourist numbers to predict visits was tested with a simple linear regression. This also failed to find a significant relationship ($F(1,7.2) = 1.9$, $p = .18$, $R^2 = 0.09$). These results suggest that locations of the cellar doors did not play a significant role in their success, but rather other elements such as offering other attractions and elements we could not test such as brand strength/reputation and promotions were more vital. Moreover, being conveniently located 'on the way' to another important tourist attraction or site, or in a sub-region with high numbers of tourists, does not necessarily result in higher cellar door visitation.

Next the frequency of co-occurrence of visits was calculated for each pair of well-visited cellar doors ($n > 8$). The R package 'cooccur' (Griffith, Veech, & Marsh, 2016), based on the pairwise co-occurrence modelling of species of Veech (2014), was used to find statistically significant pairs of cellar doors by calculating the probability that a random distribution of links would lead to greater or lower rates of co-occurrence. A few notable patterns or 'pairings' emerged, however, given the overall number of cellar doors that recorded wine tourists, this data should be viewed with caution.

As shown in Table 5, analysis of the data revealed that tourists at Cellar Door 3 were also very likely to visit Cellar Door 5 (< 0.0001 probability of greater occurrence (gt) with random distribution), which was unsurprising given their very close geographic proximity (i.e. 2 km from each other). Cellar Door 5 tourists were likely to visit Cellar Door 8 ($P(gt) = 0.004$), which is its second closest cellar door. Cellar Door 7 tourists were very likely to visit Cellar Door 4 ($P(gt) = 0.01$) and Cellar Door 6 ($P(gt) = 0.03$). However, Cellar Doors 4 and 6 did not have a significant relationship, even though these vineyards are closer in geographic distance to each other than they both are to Cellar Door 7.

Mapping these co-occurrences demonstrated that the East, West and South sub-regions were continuing to have an affect (Fig. 3). Using ArcGIS 10.5.1, the relative strength of relationship between cellar doors was shown using proportional symbology on polylines of each link based on the probability of lower co-occurrence ($P(lt)$). While closest cellar doors did not always share the highest rate of co-occurrence, all cases of significant co-occurrence occurred in pairs of cellar doors that were on the same side of the river. Cellar Door 2 was the only cellar door with co-occurrence probabilities below 0.9 with cellar doors in the same sub-region ($P(lt) = 0.57$ – 0.85). All other intra-sub-region $P(lt)$ scores were between 0.97 and 1, while inter-sub-region scores ranged from 0.05 to 0.80. Analysis of the variance between same sub-region and different sub-regions revealed that this was significant ($F(3,24) = 23.12$, $p < .001$) (Table 6).

Table 3

Length of time spent at cellar doors by Tamar Valley wine tourists, alongside observations of the cellar door.

Cellar Door (CD)	Number of wine tourists ^a	Average time spent at the CD (h:mm:ss)	Percentage of tourists who spent 'X' minutes at CD			CD located on major arterial road	Other attractions and/or facilities, in addition to standard tasting
			<10	10–30	>30		
Cellar Door 16	1	1:13:08	0	0	100	No	No
Cellar Door 19	1	0:50:49	0	0	100	Yes	No
Cellar Door 1	27	0:49:08	30.8	15.4	53.8	No	Yes
Cellar Door 9	7	0:45:51	20.0	60.0	20.0	No	Yes
Cellar Door 2	19	0:41:48	33.3	8.3	58.3	Yes	Yes
Cellar Door 8	9	0:30:16	28.6	28.6	42.9	No	Yes
Cellar Door 7	10	0:26:17	33.3	33.3	33.3	Yes	Yes
Cellar Door 3	17	0:23:55	35.3	41.2	23.5	No	Yes
Cellar Door 6	12	0:21:47	40.0	30.0	30.0	Yes	Yes
Cellar Door 13	3	0:19:10	33.3	33.3	33.3	No	No
Cellar Door 10	6	0:15:06	66.7	0.0	33.3	No	No
Cellar Door 4	15	0:11:38	45.5	45.5	9.1	No	Yes
Cellar Door 11	5	0:09:11	80.0	0.0	20.0	No	No
Cellar Door 5	14	0:06:37	75.0	25.0	0.0	No	No
Cellar Door 14	2	0:05:41	100	0	0	No	No
Cellar Door 22	1	0:05:09	100	0	0	No	No
Cellar Door 12	3	0:04:02	100	0	0	No	No
Cellar Door 21	1	0:03:22	100	0	0	No	No
Cellar Door 20	1	0:02:30	100	0	0	Yes	No
Cellar Door 15	2	0:02:16	100	0	0	No	No
Cellar Door 18	1	0:01:59	100	0	0	No	No
Cellar Door 17	1	0:01:50	100	0	0	No	No

^a This number represents the number of individual wine tourists ($n = 86$) that visited that cellar door, rather than the total number of visits or individual stops ($n = 157$).

Table 4

Comparison of minutes spent in CDs and number of visits by location and offerings.

Mann-Whitney test to compare minutes spent visiting a CD			Chi-square test to compare mean visits to a CD		
	Not on major road	On major road		Not on major road	On major road
Median	0:10:01	0:18:58	Mean	6.8	8.6
IQR	00:39:19	0:36:42	St Dev	7.21	6.89
		U = 1739.5, p = .22			X ² (1) = 0.30 p = .58
	No attractions	Attractions		No attractions	Attractions
Median	0:03:23	0:18:11	Mean	3.0	14.5
IQR	0:15:56	0:43:03	St Dev	3.42	6.08
		U = 2494.5, p < .001 ***			X ² (1) = 9.89 p = .002 ***

In summary, the findings presented here were facilitated through the GNSS capabilities of the bespoke Tourism Tracer app used for data collection. Traditional self-administered or paper-based survey research that relies on tourist's being able to recall where they have gone during their stay, may not have revealed these finer grained and nuanced details.

6. Conclusions

This paper explored the application of GNSS tracking and survey data via a bespoke app as a method of obtaining spatial-temporal behaviour data for wine tourists. To date, no prior wine tourism studies have used this approach. By using this methodology, we found that the locations of the cellar doors did not play a significant role in driving visitor behaviour, but rather other elements such as offering other attractions was significant in terms of extending the length the visitor stayed. Moreover, being conveniently located 'on the way' to another important tourist attraction or site, or in a sub-region with high numbers of tourists, does not necessarily result in higher cellar door visitation. Findings such as this demonstrate that tracking data can play a useful role in determining the percentage of tourists who visit cellar doors, compared to those who are in the region but pass by.

This study's findings also revealed several patterns in terms of the direction wine tourists travel, how far into the region they disperse, and which cellar doors typically attract single cellar door tourists versus those who attract a greater portion of wine tourists that visit multiple cellar doors during their stay. While the traditional definition of a wine tourist has been one that visits multiple cellar doors, and/or is motivated to visit a destination because of its wine experiences, our study concludes there may be far more nuanced and differentiated segments of the wine tourist, which would benefit from further research.

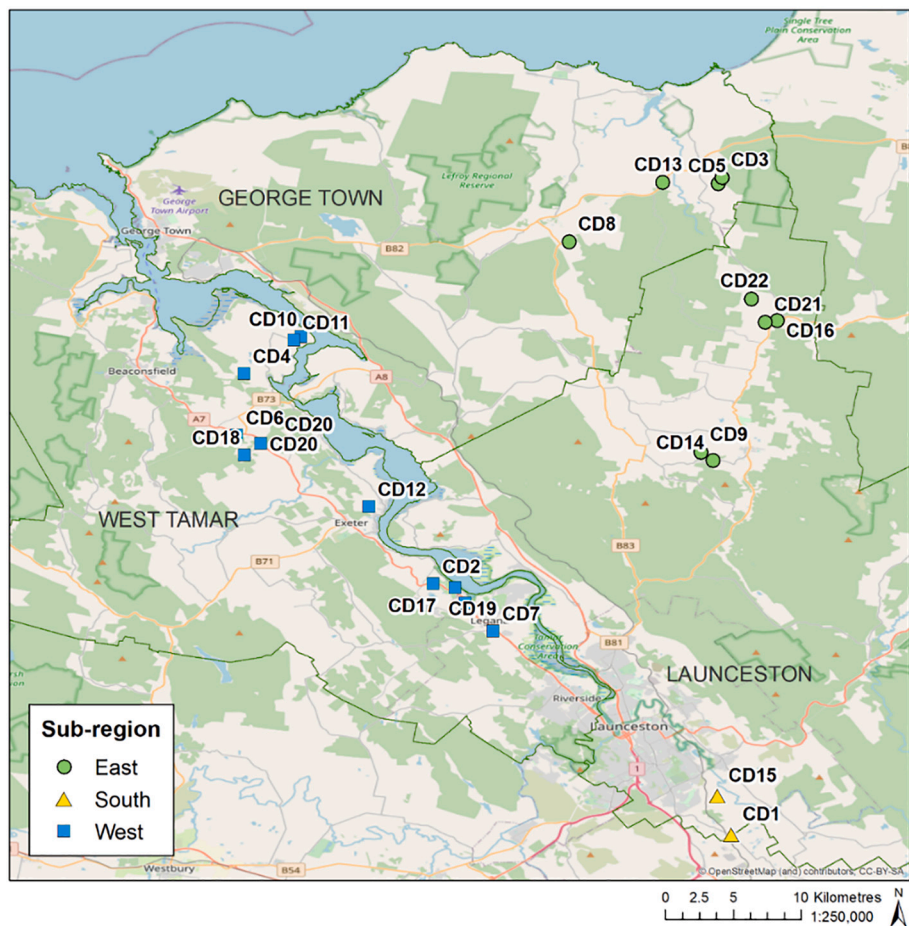


Fig. 1. Sub-regions within the Tamar Valley and cellar door locations.

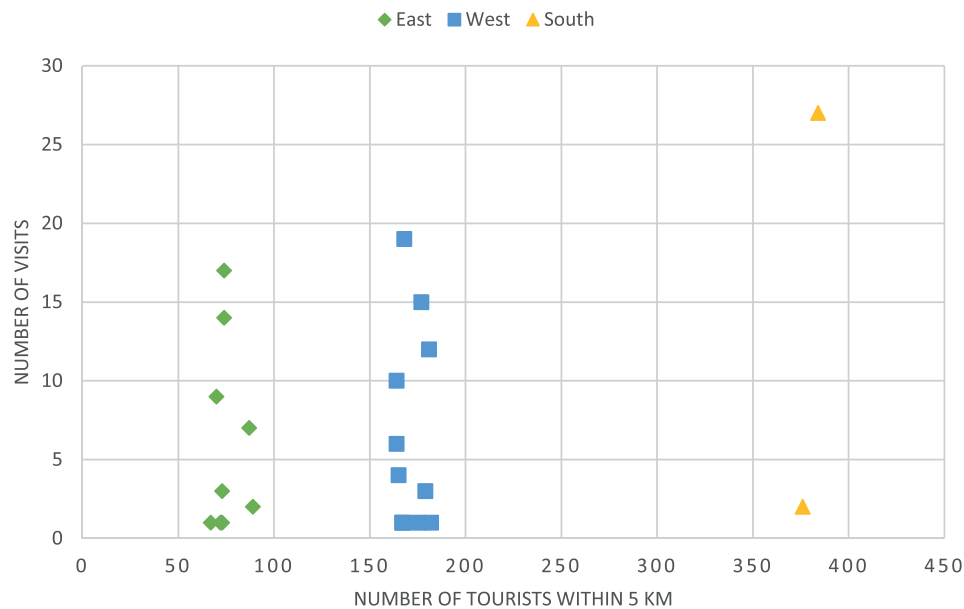


Fig. 2. Clusters of wine tourists within the sub-regions.

6.1. Methodological contributions

The findings we have presented here represent an important contribution to the understanding of wine tourist behaviour, and

foundation for further empirical work. This study also advances our understanding and appreciation of the use of mobile phone tracking as a valuable data collection method for wine tourist research. Other researchers (e.g. Hardy et al., 2017; McKercher & Li, 2009) have

Table 5

Co-occurrence for Tamar Valley cellar doors attracting wine tourists.

Cellar door pair		1st CD instances	2nd CD instances	Co-occurrence observations	Co-occurrence probability	Expected random co-occurrence	Probability lower co-occurrence	Probability greater co-occurrence	Sub-regions
Cellar Door 1	Cellar Door 2 ^a	27	19	2	0.069	6	0.02 ^a	1	SW
Cellar Door 1	Cellar Door 3 ^a	27	17	2	0.062	5.3	0.04^a	0.99	SE
Cellar Door 1	Cellar Door 4	27	15	2	0.055	4.7	0.08	0.98	SW
Cellar Door 1	Cellar Door 5	27	14	2	0.051	4.4	0.11	0.97	SE
Cellar Door 1	Cellar Door 6 ^a	27	12	0	0.044	3.8	0.01^a	1	SW
Cellar Door 1	Cellar Door 7	27	10	1	0.037	3.1	0.11	0.98	SW
Cellar Door 1	Cellar Door 8	27	9	1	0.033	2.8	0.16	0.97	SE
Cellar Door 2	Cellar Door 3	19	17	1	0.044	3.8	0.06	0.99	WE
Cellar Door 2	Cellar Door 4	19	15	3	0.039	3.3	0.57	0.70	WW
Cellar Door 2	Cellar Door 5	19	14	1	0.036	3.1	0.13	0.98	WE
Cellar Door 2	Cellar Door 6	19	12	3	0.031	2.7	0.75	0.52	WW
Cellar Door 2	Cellar Door 7	19	10	3	0.026	2.2	0.85	0.39	WW
Cellar Door 2	Cellar Door 8	19	9	2	0.023	2	0.69	0.64	WE
Cellar Door 3	Cellar Door 4	17	15	1	0.034	3	0.15	0.97	EW
Cellar Door 3	Cellar Door 5 ^b	17	14	10	0.032	2.8	1	0.000^b	EE
Cellar Door 3	Cellar Door 6	17	12	1	0.028	2.4	0.26	0.94	EW
Cellar Door 3	Cellar Door 7	17	10	2	0.023	2	0.69	0.63	EW
Cellar Door 3	Cellar Door 8	17	9	4	0.021	1.8	0.99	0.07	EE
Cellar Door 4	Cellar Door 5	15	14	0	0.028	2.4	0.05	1	WE
Cellar Door 4	Cellar Door 6	15	12	4	0.024	2.1	0.97	0.13	WW
Cellar Door 4	Cellar Door 7 ^b	15	10	5	0.02	1.7	1	0.01^b	WW
Cellar Door 4	Cellar Door 8	15	9	0	0.018	1.6	0.16	1	WE
Cellar Door 5	Cellar Door 6	14	12	0	0.023	2	0.10	1	EW
Cellar Door 5	Cellar Door 7	14	10	2	0.019	1.6	0.80	0.51	EW
Cellar Door 5	Cellar Door 8 ^b	14	9	5	0.017	1.5	1	0.005^b	EE
Cellar Door 6	Cellar Door 7 ^b	12	10	4	0.016	1.4	1	0.03^b	WW
Cellar Door 6	Cellar Door 8	12	9	1	0.015	1.3	0.63	0.76	WE
Cellar Door 7	Cellar Door 8	10	9	0	0.012	1	0.31	1	WE

^a Denotes significant negative associations.^b Denotes significant positive associations.

highlighted concerns with self-reporting and traditional surveys as a research method for obtaining insight into the movement and travel behaviour of tourists. To our knowledge, no prior study has utilised technology in this way to measure the actual behaviours and movements of wine tourists. Despite having a small sample, the current study found several significant patterns of space and time movement, and hence confirms that the tracking method used here represents a valid and reliable technique for future research in wine tourism. Moreover, this study illustrates that the combination of GNSS and survey data provides insights into mobility that cannot be accurately achieved through surveys. For example, our research is able to determine precise movement patterns before and after cellar door visits; data which is not able to be

gained via surveys that can only collect data on past behaviour and may be compromised if participants cannot recall precise details (Hardy, 2020). As a result, the following recommendations are made:

6.2. Recommendations for destination management organisations (DMOs)

At a destination level, understanding which segments of wine tourists visit certain cellar doors, in addition to how they move within local government areas, enables DMOs to develop new products and recommend more attractive wine route packages, which are based on wine tourists' spatial behaviour and preferences. Regional tourism

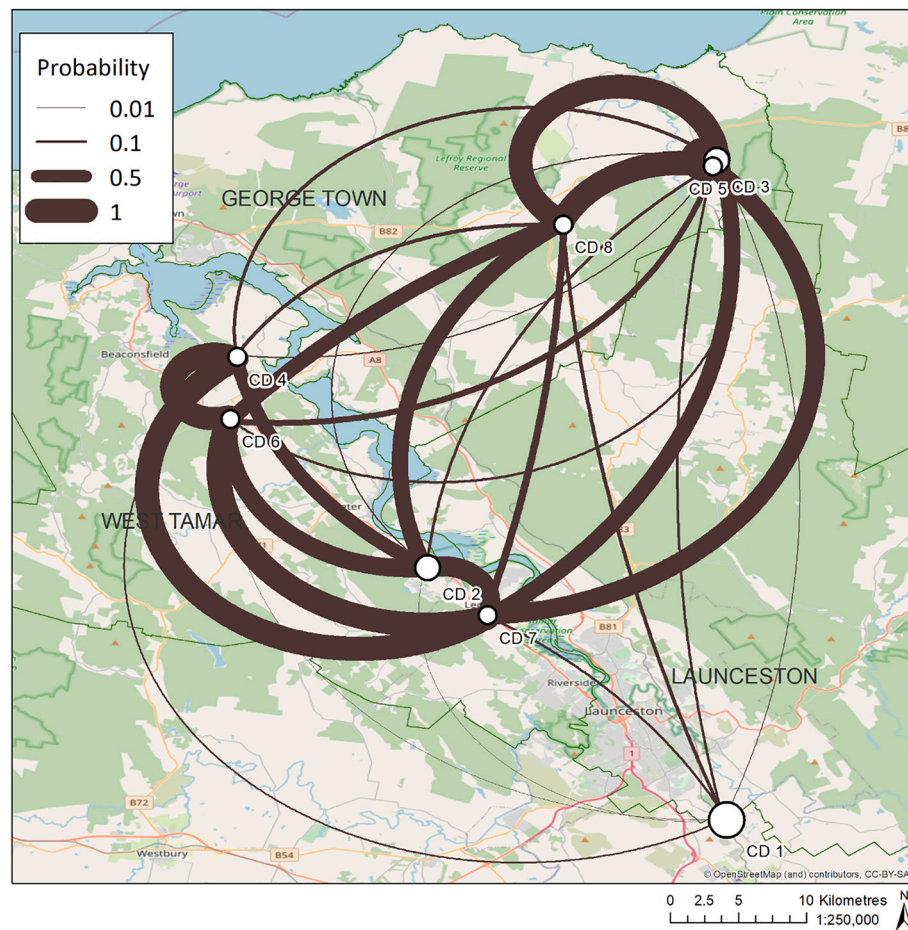


Fig. 3. Co-occurrence between cellar doors with line width used to depict probability that random distribution of links would result in lower co-occurrence.

Table 6

ANOVA results to test significance of sub-region on number of nearby tourists, number of visits, and co-occurrence relationships for cellar doors.

Sub-region	CD count	Average tourists within 5 k	Average CD visits
East	9	75.44	6.11
West	11	171.73	6.64
South	2	380.00	14.50
ANOVA df = f		(2,19) = 1553.6	(2,19) = 1.12
ANOVA P-value		0.00*	0.35
Co-occurrences	Count	Average P(lt)	Variance
East-East	3	1.00	0.00
West-West	6	0.86	0.03
East-West	12	0.34	0.08
South-East/West	7	0.08	0.00
ANOVA df = f			F(3,24) = 23.12
ANOVA P-value			0.00*

associations and DMOs frequently develop and publish suggested itineraries, and the data presented in this study could be used to develop the itineraries most likely to succeed. Knowledge of the demographic of each segment, along with their mobility could also assist such organisations to tailor their offerings and make decisions in real-time regarding who they should target.

It should be noted that as with all newly developed technology, this study was costly to roll out. However, refinement of the technology means this form of research, particularly when self-recruitment is involved, is relatively cheap to implement.

6.3. Recommendations for wine cellar door operators

From a practical perspective, our findings offer wine cellar door operators an innovative approach that can facilitate enhanced visitation, develop new tourism products, and aggregate experiences to the needs and preferences of tourists. This method enables individual wineries to plan the experiences they offer and understand how this may or may not be affected by other cellar doors their visitors are attending (for example, one with a restaurant or one with similar varieties available for tasting). For cellar doors located in peripheral areas, movement data may prove to be even more valuable if it leads to product offerings that encourage wine tourists to stay longer and spend more, as well disperse tourists further into the region.

Cellar door operators who wish to maximise return on their marketing investment can also utilise data such as this to understand who is visiting and who is driving by their business without stopping. Data of this nature can also provide a platform from which to collaborate for mutual benefit (i.e. with nearby cellar doors or tourism businesses) and assist in identifying where the gaps are in the market for products. These implications are especially important for smaller businesses, who generally operate on a limited budget and are constrained by time and other non-financial resources.

A further use for tracking data could apply to wine producers who have not yet opened a cellar door. Some wine producers are choosing to build a cellar door in an area that has visitor traffic from within their target market, rather than sticking to the traditional approach of locating the cellar door at their vineyard or winery site. Here we found that certain segments of wine tourists visit cellar doors in certain areas of a region, and potentially even at certain times of the day. This previously

unattainable knowledge could prove extremely useful when choosing the site for a cellar door, and/or deciding what other activities should be offered. Temporal data such as the time of day wine tourists typically visit, and how long they spend at each cellar door, can also be used to increase efficiencies with staffing, and the design and execution of special events and/or promotions.

Tourism businesses other than cellar doors can also interrogate our study's findings to identify what is driving tourist traffic in their region. Knowledge of visitor behaviour, their socio-demographic characteristics and their likely itineraries could assist these other businesses to tailor their offerings (e.g. opening hours) or to create collaborations (e.g. 'no corkage charge' at a local restaurant if wine is purchased from within the region).

6.4. Future research

This study was limited by a small sample size. Further research is needed with larger sample sizes to verify the accuracy of our results. There is also a need to further explore the acceptance – or not – by tourists to use this rapidly expanding method, as an alternative to surveys. There is also a pressing need to understand what types of participants take part in research such as this, where self-selection is the primary means of recruitment.

Beyond this, there are many possibilities for future research into the efficacy of the technology. For example, future research could investigate whether 'push notifications' sent to wine tourists via their mobile phone could enact certain behaviour and entice them to visit more cellar doors or follow a particular itinerary. Moreover, designing short sentiment surveys embedded within mobile apps could capture data on the tourists' wine preferences or specific questions industry are seeking, thus enabling better alignment with the marketing and branding of a wine region. It would also be interesting to measure the reputation of the winery, and the type of 'other activities' they offer, to empirically test the influence this has on visitor behaviour. Moreover, future research could apply our methodology to multiple wine regions, and in doing so, investigate the similarities and differences between different destinations and test the predictive capabilities of a wine tourist tracking approach. With technology readily available, now is an ideal time to expand this research, and in doing so develop big data sets and artificial intelligence, which advance even further our knowledge of this group of special interest tourists.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.annale.2021.100022>.

References

- Ahas, R., Aasa, A., Mark, U., & Pae, T. K. (2007). Seasonal tourism spaces in Estonia: Case study with mobile positioning data. *Tourism Management*, 28, 898–901.
- Ahas, R., Aasa, A., Roose, A., Mark, U., & Silm, S. (2008). Evaluating passive mobile positioning data for tourism surveys: An Estonian case study data. *Tourism Management*, 29, 469–486.
- Ahas, R., Silm, S., Järvi, O., Saluveer, E., & Tiru, M. (2010). Using mobile positioning data to model locations meaningful to users of mobile phones. *Journal of Urban Technology*, 17, 3–27.
- Alant, K., & Bruwer, J. (2010). Winery visitation sets: Intra-regional spatial movements of wine tourists in branded regions. *International Journal of Wine Business Research*, 22(2), 191–210.
- Alonso, A. D., Bressan, A., O'Shea, M., & Krajsic, V. (2013). Website and social media usage: Implications for the further development of wine tourism, hospitality, and the wine sector. *Tourism Planning & Development*, 10, 229–248.
- Alonso, A. D., & Liu, Y. (2010). Wine tourism development in emerging Western Australian regions. *International Journal of Contemporary Hospitality Management*, 22(2), 245–262.
- Anderson, K. (2001). Prospects ahead for the wine industry. In *CIES wine policy brief Vol. 7*. Adelaide: University of Adelaide.
- Assero, V., & Patti, S. (2011). Wine tourism experience and consumer behavior: the case of Sicily. *Tourism Analysis*, 16(4), 431–442.
- Back, R. M., Bufquin, D., & Park, J. Y. (2018). Why do they come back? The effects of winery tourists' motivations and satisfaction on the number of visits and revisit intentions. *International Journal of Hospitality & Tourism Administration*, 1–25.
- Beeco, J. A., & Hallo, J. C. (2014). GPS tracking of visitor use: Factors influencing visitor spatial behavior on a complex trail system. *Journal of Park Recreation Administration*, 32, 43–61.
- Beeco, J. A., Huang, W.-J., Hallo, J. C., Norman, W. C., McGehee, N. G., McGee, J., & Goetcheus, C. (2013). GPS tracking of travel routes of wanderers and planners. *Tourism Geography*, 15, 551–573.
- Birenboim, A., Anton-Clavé, S., Russo, A. P., & Shoval, N. (2013). Temporal activity patterns of theme park visitors. *Tourism Geographies*, 15(4), 601–619.
- Bruwer, J. (2003). South African wine routes: Some perspectives on the wine tourism industry's structural dimensions and wine tourism product. *Tourism Management*, 24, 423–435.
- Bufquin, D., Back, R. M., Park, J.-Y., & Nutta, M. (2018). The effects of architectural congruence perceptions on winery visitors' emotions and behavioral intentions: The case of Marqués de Riscal. *Journal of Destination Marketing & Management*, 9, 56–63.
- Buhalis, D., & Amaranggana, A. (2013). Smart tourism destinations. In Z. Xiang, & I. Tussyadiah (Eds.), *Information and communication technologies in tourism* (pp. 553–564). Vienna, Austria: Springer.
- Charters, S., & Ali-Knight, J. (2002). Who is the wine tourist? *Tourism Management*, 23, 311–319.
- Cox, C., & Wray, M. (2011). Best practice marketing for regional tourism destinations. *Journal of Travel & Tourism Marketing*, 28, 524–540.
- De Cantis, S., Ferrante, M., Kahani, A., & Shoval, N. (2016). Cruise passengers' behavior at the destination: Investigation using GPS technology. *Tourism Management*, 52, 133–150.
- Edwards, D., & Griffin, T. (2013). Understanding tourists' spatial behaviour: GPS tracking as an aid to sustainable destination management. *Journal of Sustainable Tourism*, 21, 580–595.
- ESRI. (2011). *ArcGIS Desktop: Release 10*. Redlands, CA: Environmental Systems Research Institute.
- Galloway, G., Mitchell, R., Getz, D., Crouch, G., & Ong, B. (2008). Sensation seeking and the prediction of attitudes and behaviours of wine tourists. *Tourism Management*, 29, 950–966.
- Getz, D., & Brown, G. (2006). Critical success factors for wine tourism regions: A demand analysis. *Tourism Management*, 27, 146–158.
- Gómez, M., González-Díaz, B., & Molina, A. (2015). Priority maps at wine tourism destinations: An empirical approach in five Spanish wine regions. *Journal of Destination Marketing & Management*, 4, 258–267.
- Gretzel, U., Sigala, M., Xiang, Z., & Koo, C. (2015). Smart tourism: Foundations and developments. *Electronic Markets*, 25, 179–188.
- Griffith, D. M., Veech, J. A., & Marsh, C. J. (2016). Cooccur: Probabilistic species co-occurrence analysis in R. *Journal of Statistical Software*, 69(1), 1–17.
- Grinberger, Y., Shoval, N., & McKercher, B. (2014). Typologies of tourists' time-space consumption: A new approach using GPS data and GIS tools. *Tourism Geography*, 16, 105–123.
- Hall, C. M., Sharples, L., Cambourne, B., & Macionis, N. (Eds.). (2000). *Wine tourism around the world: Development, management and markets*. Oxford: Butterworth-Heinemann.
- Hallo, J. C., Beeco, J. A., Goetcheus, C., McGee, J., McGehee, N. G., & Norman, W. C. (2012). GPS as a method for assessing spatial and temporal use distributions of nature-based tourists. *Journal of Travel Research*, 51(5), 591–606.
- Hardy, A. (2020). *Tracking tourists: Movement and mobility*. London: Goodfellow Publishers.
- Hardy, A., & Aryal, J. (2020). Using innovations to understand tourist mobility in national parks. *Journal of Sustainable Tourism*, 28(2), 263–283.
- Hardy, A., Birenboim, A., & Wells, M. P. (2020). Using geoinformatics to assess tourist dispersal at the state level. *Annals of Tourism Research*, 82.
- Hardy, A., Hyslop, S., Booth, K., Robards, B., Aryal, J., Gretzel, U., & Eccleston, R. (2017). Tracking tourists' travel with smartphone-based GPS technology: A methodological discussion. *Information Technology & Tourism*, 17(3), 255–274.
- Lewis, G. K., Byrom, J., & Grimmer, M. (2015). Collaborative marketing in a premium wine region: The role of horizontal networks. *International Journal of Wine Business Research*, 27, 203–219.
- Lewis, G. K., & Lehman, K. (2020). Culture and the visitor experience: A way forward for wine tourism in Tasmania. In C. S. Ooi, & A. Hardy (Eds.), *Tourism in Tasmania* (pp. 137–148). Hobart: Forty South Publishing Pty Ltd.
- Li, J., Xu, L., Tang, L., Wang, S., & Li, L. (2018). Big data in tourism research: A literature review. *Tourism Management*, 68, 301–323.

- Lindgreen, A. (2001). An exploration of contemporary marketing practices in the New Zealand wine sector. *International Journal of Wine Marketing*, 13, 5–22.
- Lindgreen, A. (2008). *Managing market relationships: Methodological and empirical insights*. Vermont, USA: Gower Publishing.
- McKercher, B., Hardy, A., & Aryal, J. (2019). Using tracking technology to improve marketing: Insights from a historic town in Tasmania, Australia. *Journal of Travel and Tourism Marketing*, 36, 823–834.
- McKercher, B., & Li, G. (2009). Methodological considerations when mapping tourist movements in a destination. *Tourism Analysis*, 14, 443–455.
- McKercher, B., Shoval, N., Ng, E., & Birenboim, A. (2012). First and repeat visitor behaviour: GPS tracking and GIS analysis in Hong Kong. *Tourism Geography*, 14, 147–161.
- Mintel. (2017). Wine tourism – 2017. Retrieved April 15, 2020, from <http://www.academicwino.com/2018/11/wine-tourism.html/>.
- Mitchell, R., Charters, S., & Albrecht, J. N. (2012). Cultural systems and the wine tourism product. *Annals of Tourism Research*, 39(1), 311–335.
- Modsching, M., Kramer, R., Hagen, K. T., & Gretzel, U. (2008). Using location-based tracking data to analyze the movements of city tourists. *Information Technology Tourism*, 10, 31–42.
- Nella, A., & Christou, E. (2014). Segmenting wine tourists on the basis of involvement with wine. *Journal of Travel & Tourism Marketing*, 31, 783–798.
- New Zealand Winegrowers Inc. (2018). *Annual Report 2018*, 1–52. Retrieved April 15, 2020, from <https://www.nzwine.com/media/9567/nzw-annual-report-2018.pdf>.
- Oosterlinck, D., Benoit, D. F., Baecke, P., & Van de Weghe, N. (2017). Bluetooth tracking of humans in an indoor environment: An application to shopping mall visits. *Applied Geography*, 78, 55–65.
- Park, J.-Y., Bufquin, D., & Back, R. M. (2019). An examination of the relationships among winery tourists' satisfaction, repeat visits and revisit intentions. *Journal of Destination Marketing & Management*, 11, 231–239.
- Pettersson, R., & Zillinger, M. (2011). Time and space in event behavior: Tracking visitors by GPS. *Tourism Geography*, 13, 1–20.
- Popp, L., & McCole, D. (2016). Understanding tourists' itineraries in emerging rural tourism regions: The application of paper-based itinerary mapping methodology to a wine tourism region in Michigan. *Current Issues in Tourism*, 19, 988–1004.
- Pratt, M. (2014). Four wine tourist profiles. In *Proceedings of the 8th International Academy of Wine Business Research Conference, June 28th – 30th, 2014, Geisenheim, Germany* (pp. 970–980).
- Pratt, M. (2019). The image of a wine tourist and impact on self-image congruity. In M. Sigala, & R. N. S. Robinson (Eds.), *Wine tourism destination management and marketing* (pp. 45–65). Cham: Palgrave Macmillan.
- R Core Team. (2021). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing. URL <http://www.R-project.org/>.
- Raun, J., Ahas, R., & Tiru, M. (2016). Measuring tourism destinations using mobile tracking data. *Tourism Management*, 57, 202–212.
- Reinhold, S., Laesser, C., & Beritelli, P. (2018). The 2016 St. Gallen consensus on advances in destination management. *Journal of Destination Marketing & Management*, 8, 426–431.
- Shoval, N., & Isaacson, M. (2010). *Tourist mobility and advanced tracking technologies*. London: Routledge.
- Shoval, N., McKercher, B., Ng, E., & Birenboim, A. (2011). Hotel location and tourism activity in cities. *Annals of Tourism Research*, 38, 1594–1612.
- Sigala, M. (2019a). Building a wine tourism destination through cooptation: The business model of ultimate winery experiences Australia. In M. Sigala, & R. N. S. Robinson (Eds.), *Wine tourism destination management and marketing* (pp. 99–112). Cham: Palgrave Macmillan.
- Sigala, M. (2019b). Introduction: Wine destination management and marketing—Critical success factors. In M. Sigala, & R. N. S. Robinson (Eds.), *Wine tourism destination management and marketing* (pp. 1–6). Cham: Palgrave Macmillan.
- Sparks, B. (2007). Planning a wine tourism vacation? Factors that help to predict tourist behavioural intentions. *Tourism Management*, 28, 1180–1192.
- The Australian and New Zealand Wine Industry Directory. (2019). *The Australian and New Zealand Wine Industry Directory 2019*, 1–578. Retrieved April 15, 2020, from <https://winetitles.com.au/statistics-2/wine-companies/>.
- Veech, J. A. (2014). The pairwise approach to analysing species co-occurrence. *Journal of Biogeography*, 41(6), 1029–1035.
- Versichele, M., de Groote, L., Bouuaert, M., Neutens, T., Moerman, I., & Van de Weghe, I. (2014). Pattern mining in tourist attraction visits through association rule learning on Bluetooth tracking data: A case study of Ghent, Belgium. *Tourism Management*, 22, 67–81.
- Wickham, H., François, R., Henry, L., & Müller, K. (2019). dplyr: A grammar of data manipulation. In *R package version 0.8.0.1*. Retrieved March 1, 2021, from <https://CRAN.R-project.org/package=dplyr>.
- Wilken, R. (2014). Places nearby: Facebook as a location-based social media platform. *New Media in Society*, 16, 1087–1103.
- Wine Tasmania. (2020). *2020 Tasmanian Vintage Report*. Retrieved November 1, 2020, from <https://winetasmania.com.au/news/2020-tasmanian-vintage-quality-up-quantity-down#:~:text=%E2%80%9COverall%2C%20yields%20were%20down%20approximately,12%2C308%20tonnes%20produced%20in%202020.%E2%80%9D>.
- Yuan, J., Morrison, A. M., Cai, L. A., & Linton, S. (2008). A model of wine tourist behaviour: A festival approach. *International Journal of Tourism Research*, 10(3), 207–219.
- Yun, H., & Park, M. (2015). Time-space movement of festival visitors in rural areas using a smart phone application. *Asia Pacific Journal of Tourism Research*, 20, 1246–1265.