Estimating temporary populations: a systematic review of the empirical literature

Radoslaw Panczak, Elin Charles-Edwards, Jonathan Corcoran

# Background

Conventional population estimates capture a population at a single point in time. Such estimates ignore the short-term dynamism of many populations caused by temporary population mobility, territorial movement which does not result in a permanent change of usual residence (Bell and Ward [2000](#ref-bellComparingTemporaryMobility2000)). Temporary population movements are defined as moves of one or more night’s duration, but can be broadened to include diurnal movements such as daily commuting (Smith [1989](#X5d18d719e819976492524d0b6418e90ee55777d)). Temporary mobility can have a large impact on the size and composition of small area populations (Charles-Edwards and Panczak [2018](#Xb06a0e7b4af98e29fbb35fb88a1cad7b6630f34)) impacting traffic, housing, retail sales, medical services and emergency preparedness to name a select few (Smith [1989](#X5d18d719e819976492524d0b6418e90ee55777d); Smith and House [2007](#ref-smithTemporaryMigrationCase2007)). As a consequence, there is growing interest and need for temporary population estimates across a broad range of purposes including the planning and delivery of goods and services, fiscal equalisation (Graebert, Wyckoff, and Bretz [2014](#X590de3fbaf7cd79061325b9c513d8723b1f966e)), retail analysis, transport demand, emergency preparedness, and as better denominators for crime and epidemiological models (Charles-Edwards et al. [n.d.](#Xf9990a8be581a58576ed12142d89533c13b9be5)).

Scholarship concerned with developing the conceptual aspects of temporary populations has seen a longstanding interest with early work appearing in the Unites States in the 1950s (Foley [1954](#ref-foleyUrbanDaytimePopulation1954); Schmitt [1956](#X976f8b8d0470b74b89fd49c81c0666197cb4976)). This early work proposed building on traditional demographic approaches to generate temporary population estimates and was first to recognise the potential value of symptomatic data as a source for such statistics. Several decades later it was Smith ([1987](#ref-smithHowTallyTemporary1987), [1989](#X5d18d719e819976492524d0b6418e90ee55777d)) that proposed set of metrics (visitor-days and visitor-years) to capture measures of population present as well as highlighting the difficulty of validating estimates of temporary populations. More recently, Bell ([2000](#ref-bellDataTheoryMethod2000), [2004](#ref-bellMeasuringTemporaryMobility2004)) argued that estimates of temporary populations are contingent on developing a rigorous understanding of temporary population mobility. Here he drew attention to four dimensions (movement intensity, duration, seasonality and spatial impact) which he argued are associated with temporary mobility and that drive the change in stock of temporary visitors at both the origin and at the destination.

Despite growing interest in temporary population statistics, they still do not form part of the standard suite of any official population statistics. Historically, this been due to a lack of data capturing temporary populations, but also nascent conceptualisation of temporary populations and lack of standard methodologies for their production. Indeed, Smith ([1989](#X5d18d719e819976492524d0b6418e90ee55777d)), in his seminal paper on the estimation of temporary populations, noted that the development of a methodology applicable across a wide range of population and scenarios was ‘most likely impossible’. He could not have predicted the proliferation of geo-located data from mobile phones and other technologies in the 21st Century with potential for the sensing of temporary populations across large geographic areas and in widely differing contexts. The current study assesses progress in the field of temporary population statistics. To this end, we conduct a systematic review of the international literature on the estimation of temporary populations to identify the contemporary state of the art. To this end the study seeks to understand the volume, geography, population coverage along with the data and methods used to generate temporary population estimates, and investigate how such estimates might be reconciled alongside traditional population statistics.

The remainder of the paper is structured as follows: In Section 2 we detail the adopted methods including information sources and search terms, eligibility criteria and data extraction. In Section 3, we report results of the review examining both theoretical and applied work. In the final sections of the paper we summarise the current start of the art and make a series of recommendations for the production of temporary population statistics.

# Methods: Protocol and capture

The review was conducted using the principles of the PRISMA Statement for Reporting Systematic Reviews (Moher et al. [2009](#ref-moherPreferredReportingItems2009)) (*Appendix 1*). In order to deal with complexity and lack of standarization in the field and to account for theory-building character of this work we additionally adopted “mixed-method review” methodology (Gough [2015](#ref-goughQualitativeMixedMethods2015)). That allowed us to combine methods of a systematic review (selection of keywords and sources, eligibility criteria, etc.) with the openness and flexibility of traditional reviews. The study was conducted without a review protocol.

Articles that form the basis of the review were captured via search of four databases; (1) Web of Science; (2) Scopus; (3) Google Scholar; and, (4) arXiv. All databases were searched using a set of keywords that collectively encompass the breadth of synonyms for temporary populations. More specifically we employed a suite of terms that were derived from the authors existing knowledge of the field, as well as key terms that emerged during early stages of the review process. Terms included: “temporary population”, “working population”, “daytime population”, “mobile population”, “service population”, “floating population”, “elusive population”, “ambient population”, “seasonal population”, “non-resident population”, “real-time census”, “social sensing” and “spatiotemporal population”. We additionally scrutinised the reference lists of included studies to ensure full coverage of articles. Last searches were conducted on the 24 November 2017. In order to to enhance the currency and coverage of the articles captured we adopted some of the principles of living systematic review methodology (Elliott et al. [2014](#ref-elliottLivingSystematicReviews2014)). We set up and reviewed updates from three of the databases covering all queries, and manually searched the fourth one. The final inclusion of studies into the review was conducted on 10 July 2019. *Appendix 2* contains details of the search strategy.

To supplement the key search terms listed above, inclusion and exclusion criteria were developed. These included:

* Studies were included if they produced estimates or forecasts of temporary populations.
* Studies were required to detail their methodology for at least one geographical region and capture non-resident populations.
* Studies were excluded if they focused their analyses on certain population bases (for instance, social media or mobile phone users) without any extrapolation to the total population of a region.
* Studies estimating tourist arrivals and crowds were also excluded given that our interest here is on studies aiming to establish more complete and stable populations in the areas in contrast to subgroups (such as tourists) or highly transient populations (such as crowds or pedestrians).
* Book reviews and magazines were excluded.
* Only studies published in English were included.

These criteria were designed to capture studies that offered in-depth empirical analysis of temporary population estimation rather than either theoretic development/debate or studies that presented descriptive analyses. Beyond the aforementioned criteria, there were no restrictions based on publication date, or publication status (for example, a published article versus an unpublished thesis). In cases where the same or similar methodology was used in several studies we selected one representative article to present in the review and collected further references in supplementary materials.

We developed data extraction sheet and revised it iteratively during the extraction process until it was applicable to all studies. One author (RP) extracted data independently. Information extracted from the studies was split into two major groups and included:

1. Publication details: Publication metadata included: authors, title, source, year and publication type. We classified studies according to the primary source of data: mobile phones (MP), remote sensing (RS), social media (SM), transport (e.g. cordon counts, traffic and smart card data), administrative data (e.g. national censuses, health care records or various registries such as a registry of second homes), surveys (e.g. time use survey, holiday accommodation occupancy surveys), Wi-Fi and data from utility providers (e.g. electricity consumption). Studies could belong to more than one category.
2. Estimation: characteristics of estimates in the study including whether estimates captured daytime or overnight populations, the country and region for which estimates were made, data sources, methods and software, data and population size, number of spatial and temporal units, validation of estimates and the purpose for which they were produced.

# Results and Discussion: Estimating temporary populations

## Publications time frame, sources and reasons for estimates

Collectively, our initial search strategy initially identified around 22.9 thousands documents (Figure 1). After removing duplicates, titles and abstracts were screen for eligibility resulting in the set of 122 articles. The final stage involved a screening of full texts resulting in the removal of a further 68 articles. Additional 27 articles were identified from other sources and 15 - captured by scaning updates of the search results. A total of 96 studies were taken forward to form part of the analysis (*Appendix 3*).

The 96 studies were published between 1925 and 2019 (median publication year 2011) and focused on various aspects of temporary population estimation, including the production of temporary population statistics (Table 1; *Appendix 4*). There has been exponential growth in the number of studies since the first publication in 1925, with more than third of the studies (34.4%) published since 2015. A total of 56.2% of studies were published as articles followed by 21.9% as reports and 11.5% as conference proceedings or presentations.

The following discussion draws on the content of the included papers that are cited throughout the text as required. Emergency planning (n=22) was the most frequently quoted as reason for producing temporary population estimates followed by understanding service populations (n=8), epidemiology (n=4) and commuting (n=3), many studies directly discussing a domain of application. We next discuss the papers under 6 broad domains; (1) data; (2) methods; (3) the geography of estimates; (4) temporal units; (5) population size and composition; and, (6) reproducibility.

## Data types

Administrative data, defined as large scale data collected by official agencies (such as censuses or registries), formed the basis or were the strong component of the largest number of studies (Figure 2). First report was based on the 1921 Census data from England and Wales and used data on place of work to estimate daytime population (Census of England and Wales 1921 [1925](#X22aea630df698ae90d2cf99bd51ca6956c40a9a)). These estimates continue to be delivered with the latest Census also offering workday population estimates for England and Wales [Office for National Statistics ([2013](#X431ee23a398248e65992ae17038ebcc49843683)); see also related work in *Appendix 5*]. Census data from the United Kingdom were also extensively used as a part of methodologies developed by more recent work of (Smith et al. [2005](#ref-smithNationalPopulationData2005)) and (Martin, Cockings, and Leung [2015](#Xbd8ddfd0df256b52fe8cc70d74f930db110bb54)).

The equivalent of this work in the United States employ commuter-adjusted population estimates using the American Community Survey to adjust night-time population counts (McKenzie et al. [2013](#Xe7167b8f9922234a11e6c172cebe4674e0af56f)). Other primarily Census-based studies from the United States include the work from the Seattle City Planning Commission ([1951](#X58da7d089538c97d533016cab4e39ff2c68bdad)) and Bureau of the Census ([1956](#Xcbd04fe0937e2be3c5b057c1e5258a48585049a)), Fulton ([1984](#X7d97b6c7c76acd4e873f8e6a5af7a6f9f389f38)), Gober and Mings ([1984](#X7648e8f10e9fcb36e4c31952887f83eba2de11b)), Nelson and Nicholas ([1992](#X8604f0b9856db05c9334a4c63598cf430b07993)), McPherson and Brown ([2003](#ref-mcphersonDayNightPopulation2003)), Kobayashi, Medina, and Cova ([2011](#X7dce184c7d2ffa719994285b937cf340dd99449)), Swanson and Tayman ([2011](#ref-swansonEstimatingFactoPopulation2011)), Hodur and Bangsund ([2015](#ref-hodurServicePopulationEstimates2015)), Kim and Ahn ([2017](#ref-kimModellingDaytimePopulation2017)), Boeing ([2018](#ref-boeingEstimatingLocalDaytime2018)) and Esri ([2018](#ref-esriMethodologyStatement20182018)). Each used a wide selection of methods to adjust Census estimates on variety of scales, often accompanied by other data sources. This for example includes, location of work, transportation models or payroll data that helps to determine size and location of daytime or seasonal population.

Census data were also used for estimation and analyses of temporary populations in Australia. Taking advantage of the availability of the place of residence and place of enumeration Bell and Ward ([1998](#ref-bellPatternsTemporaryMobility1998)) (see also subsequent work in *Appendix 5*) looked at the one day snapshot of mobility of Australians across different years and scales whereas Taylor ([1998](#ref-taylorMeasuringShortTerm1998)) used Census for the estimation of mobility of indigenous people. Finally Gao et al. ([2014](#ref-gaoAssessingSocialEconomic2014)) used Chinese Census data adjusted with figures for tourists, school and patient populations and Qi et al. ([2015](#ref-qiModelingSpatialDistribution2015)) extended it with land use models.

Census main advantage is that it provides close to full enumeration of the population, however it also provides only a snapshot of temporary populations on one day or night, every five or ten years. Many form of temporary population mobility are highly seasonal, thus census data will not reflect the population present at other times of the year. Finally, other forms of administrative data such as health service utilization records (Markham, Bath, and Taylor [2013](#ref-markhamNewDirectionsIndigenous2013)), building (Greger [2015](#X0e70fc066386bd8923e1e1bea7c880bd567f6b7)) or second home registries (Adamiak, Pitkänen, and Lehtonen [2017](#X1c6c72b80b9275feebacb0744e344ee957ad507)) often complement census providing another data source for methods estimating temporary populations.

The second most frequent group of studies was based on data coming from wide array of surveys. The early work from United States can be traced back to the work of Thornthwaite who estimated daytime population of a Central Business District using trafic survey ([1929](#Xd3615397e1baf5f2f392fce68669c2bdc265e73); cited in Wheeler and Brunn [2002](#ref-wheelerUrbanGeographerHis2002)). Others followed including Breese ([1947](#ref-breeseDaytimePopulationCentral1947)), Sharp ([1955](#X2e7fbda3227d8805800c75beca7aa361f035a59)) and Weir ([1960](#ref-weirSurveyDaytimePopulation1960)). The New York Regional Plan Association ([1949](#X4d0b260e50b91ec14e6d4e99bcfa563023758f4)), Seattle City Planning Commission ([1951](#X58da7d089538c97d533016cab4e39ff2c68bdad)) and Institute for Research in Social Science at the University of North Carolina ([1952](#Xd261d8200194e091ef22059381e31978f2f087b)) employed various sources of transportation surveys and cordon counts to estimate number of people in central business districts. Similar work from UK was done by Menzler ([1952](#ref-menzlerEstimateDaytimePopulation1952)). All these early effort relied on relatively simple methods and working with various survey data, often transport related (cordon counts, traffic surveys) but sometimes surveying whole resort town (Erickson [1961](#Xdab9ae9757eb5f474e300a0e4a32b1b00177871)) or areas with significant concentrations of temporary residents (Happel and Hogan [2002](#Xf2b6ef32229490c6fb183f2e033228e301d52f7)). Many of these conceptual approaches have been updated and developed further with various other types of surveys including travel surveys in multiple locations (Charles-Edwards [2011](#X361b47fae96f046db90e9d5f0a52cf729966927); Collins and Greaves [2007](#ref-collinsDaytimePopulationTracking2007); Himoto and Kimata [2014](#X27e3641eb69f23f8e455fb49d5e3998812709c0); Horanont and Shibasaki [2010](#X28d15360b5aceee963a70affbe8608e3e1a1a45); Kashiyama, Pang, and Sekimoto [2017](#ref-kashiyamaOpenPFLOWCreation2017); Kavanaugh [1990](#ref-kavanaughMethodEstimatingDaytime1990); Lau [2009](#ref-lauGISBasedStochastic2009); Roddis [1996](#Xe8bb5c0fef8c10e21d7377d3731ca253db22ff5); Sekimoto et al. [2011](#X7f91b814f5d3017f8d862be126d6349e345a1c3); Stutz, Parrott, and Kavanaugh [1992](#ref-stutzChartingUrbanSpacetime1992); Wurtele and Wellisch [1968](#ref-wurtelePopulationDynamicsFinal1968)) as well as more traditional, telephone surveys (Galvez and McLarty [1996](#X146b4c4558660916e3ef5d4ac59087f73f6413b)) or specific surveys such as counts of indigenous population (Warchivker, Tjapangati, and Wakerman [2000](#Xae5061268a46a2c7270dac14d859c96c0d7e4a6)), all complimenting data sources for estimation of temporary populations.

Although censuses and surveys tend to lose their position as primary source of data, they still remain crucial part of many estimation attempts. There is a shift from using them as primary sources and into providing more complimentary role, for instance serving as starting points for estimation (–for example, serving as ‘night time population’), delivering time use profiles used to redistribute other data or calibrate models or as a source of validation. For instance, seminal work of LandScan (Bhaduri et al. [2007](#ref-bhaduriLandScanUSAHighresolution2007)) used Census as one of the main inputs and Ma et al. ([2017](#ref-maModelingHourlyDistribution2017)) used smart card data to redistribute census (night) counts of population across city.

Third largest category of studies, and one that experienced the fastest growth in recent years, is work based on mobile phone (MP) data. The earliest identified application of MP data to estimate temporary populations was done in response to Haiti earthquake (Bengtsson et al. [2011](#Xb874d7e72bc1fd03b939d1ecbb0748060174c7a)). That was quickly followed by large scale estimates for Japan (Terada, Nagata, and Kobayashi [2013](#X673334009c0611aa61cf0dec5af9f6d5b21025a)) and analyses of temporary populations in France and Portugal (Deville et al. [2014](#ref-devilleDynamicPopulationMapping2014)). Spatial coverage of MP based studies often reflects availability and accessibility of data. For instance, Italy and in particular Milan, are the subject of a number of studies due to the fact that local providers offer access to the aggregated and anonymized call detail records (CDR) (Khodabandelou et al. [2016](#Xefa36958271c704f945031f12b3b6b0ef8d6a2c)). MP data are also used in parallel with other sources and methods for instance in dasymetric interpolation (Järv, Tenkanen, and Toivonen [2017](#ref-jarvEnhancingSpatialAccuracy2017)) or together with transport survey data (Lwin, Sugiura, and Zettsu [2016](#ref-lwinSpaceTimeMultiple2016)).

Less common, yet still significant are studies were based on utilities data (Edmondson and Nantucket Data Platform team [2019](#ref-edmondsonMakingItCount2019); Goldschmidt and Dahl [1976](#Xc732fd1c877ed49ac82863c198b15b359f96233); McKenzie and Canterford [2016](#ref-mckenzieDemographicsFireRisk2016); Monmouth County Planning Board [2008](#X03e12ef096b2675b4a1945552df4a4d078879a6); Rigall-I-Torrent [2010](#Xad34659e5420cd9693886e69b642761ab2baf66)), remote sensing (Stathakis and Baltas [2018](#X5e026a61cde6489b9c4a42fd8ace1c75d70f441); Taubenböck, Roth, and Dech [2007](#ref-taubenbockLinkingStructuralUrban2007)) and Wi-Fi (Crols and Malleson [2019](#X989233a17de95d7d128e49a9cf34507da49f97a); Kontokosta and Johnson [2017](#ref-kontokostaUrbanPhenologyRealtime2017)). Contrary to our expectations, social media (SM) data were only used by one study (Lwin, Sugiura, and Zettsu [2016](#ref-lwinSpaceTimeMultiple2016)). Recognition of complexity of providing estimates together with growing availability of data also led to attempts combining multiple sources of data (Fehr & Peers [2014](#ref-fehrpeersNapaCountyTravel2014):@edmondsonMakingItCount2019).

## Estimation methods

The earliest method of deriving temporary population statistics was to use direct estimates, either from the Census (Census of England and Wales 1921 [1925](#X22aea630df698ae90d2cf99bd51ca6956c40a9a)), survey (Thornthwaite [1929](#Xd3615397e1baf5f2f392fce68669c2bdc265e73)) or by combining multiple formerly disparate sources of data (Breese [1947](#ref-breeseDaytimePopulationCentral1947)). These studies took advantage of availability of information about workplaces of individuals (Office for National Statistics [2013](#X431ee23a398248e65992ae17038ebcc49843683)), their status of residence (Gober and Mings [1984](#X7648e8f10e9fcb36e4c31952887f83eba2de11b)) or place of enumeration (Bell and Ward [1998](#ref-bellPatternsTemporaryMobility1998)) to distinguish between two or more states of population distribution such as night- and daytime.

Alternative approaches used some form of scaling of population counts from one or more sources to the whole population either by using expansion factors. Such approaches were used by both early surveys (Foley [1952](#ref-foleyDailyMovementPopulation1952); New York Regional Plan Association [1949](#X4d0b260e50b91ec14e6d4e99bcfa563023758f4)) and more contemporary analyses based on MP or Wi-Fi data. In the latter case, various strategies of deriving factors were adopted, some based on penetration rate of MP data provider (Bengtsson et al. [2011](#Xb874d7e72bc1fd03b939d1ecbb0748060174c7a)), night-time Census population (Deville et al. [2014](#ref-devilleDynamicPopulationMapping2014)) or ancillary survey data (Kontokosta and Johnson [2017](#ref-kontokostaUrbanPhenologyRealtime2017)). Studies either used a single factor for entire region (Thomas et al. [2017](#ref-thomasUseMobileDevice2017)) or multiple ones, varying them geographically (Batran et al. [2018](#X44578f94e9a82c77fc23a3667a8de2230119dba)) or over subgroups of population (Picornell et al. [2018](#ref-picornellPopulationDynamicsBased2018)).

A separate strand of research focused on various methods to redistribute temporary populations in larger spatial units to smaller ones. A range of methods are used including dasymetric approaches widely used for mapping small area resident populations. LandScan USA model (Bhaduri et al. [2007](#ref-bhaduriLandScanUSAHighresolution2007)) for instance has the largest spatial coverage providing gridded population estimates of the nightime and daytime population for the United States. Martin et al. ([2015](#Xbd8ddfd0df256b52fe8cc70d74f930db110bb54)) model for Southampton on the other hand is an example of more spatially and temporally detailed approach that can be adapted to various grid sizes and temporal resolutions and has been implemented in other locations and settings (*Appendix 5*). The redistribution approach usually uses ancillary data such as land use (Batista e Silva et al. [2017](#Xd64112570534a5277069b2199bcf274d467db35)) or building type (Greger [2015](#X0e70fc066386bd8923e1e1bea7c880bd567f6b7)) and apart from Census or surveys could also use MP (Järv, Tenkanen, and Toivonen [2017](#ref-jarvEnhancingSpatialAccuracy2017)) or transportation data (Ma et al. [2017](#ref-maModelingHourlyDistribution2017)) as input.

Temporary populations were also estimated using various equation-based population accounts. These methods used generic or area-specific equation to derive counts of temporary residents from usual residents, subtracting departures and adding arrivals to a spatial unit in given time (Yong li [1998](#ref-yongliResearchStatisticalModels1998)). For instance Journey-to-Work data is used to estimate the working population (McKenzie et al. [2013](#Xe7167b8f9922234a11e6c172cebe4674e0af56f)), second home users and usage could be used to capture seasonal populations in specific areas (Adamiak, Pitkänen, and Lehtonen [2017](#X1c6c72b80b9275feebacb0744e344ee957ad507)) or sales tax data could be used to derive equivalent residents (Thakur [2018](#ref-thakurMethodologyAccountSeasonal2018)). Additionally, separate estimates could be derived for subgroups of population (Swanson and Tayman [2011](#ref-swansonEstimatingFactoPopulation2011)) or for temporal units using seasonal coefficient derived from night-time satellite imagery (Stathakis and Baltas [2018](#X5e026a61cde6489b9c4a42fd8ace1c75d70f441)).

Finally, large number of modelling and simulation approaches were tested more recently with various forms of data inputs. That ranged from agent based simulation (Crols and Malleson [2019](#X989233a17de95d7d128e49a9cf34507da49f97a); Kashiyama, Pang, and Sekimoto [2017](#ref-kashiyamaOpenPFLOWCreation2017); Walker and Barros [2012](#ref-walkerAgentbasedPopulationModel2012)), cellular automaton model (Khakpour and Rød [2016](#X04eb2891d8407e9bbb1747320f317539e68e99c)), to the use of neural networks (Chen et al. [2018](#ref-chenFinegrainedPredictionUrban2018); Liu et al. [2018](#ref-liuMappingHourlyDynamics2018)).

## The geography of estimates

Only 17.7% of studies reported on estimates created for the whole country (Figure 3). The United States was the most represented with a total of five studies, followed by Australia and England and Wales. Only one developing country, Nepal, (Wilson et al. [2016](#ref-wilsonRapidRealTimeAssessments2016)) was represented and one study reported on two countries (Deville et al. [2014](#ref-devilleDynamicPopulationMapping2014)). Studies covering a part of the country were again most frequent in the United States. This was followed by China, Australia, Japan and the United Kingdom. A handful of developing nations [Haiti, Bangladesh, Mozambique, Myanmar and Vietnam] were included as well. A little more than half (53.1%) of the studies were focused on a single city.

Two types of spatial unit for the estimates dominated; 58.3% of studies used some form of administrative units (for example, statistical division, county, township or entire city) and 28.1% used grids of varying sizes. Other types of spatial unit included individual points or nodes or Vornoi polygons. A number of studies (n=11) reported estimates for more than one type of spatial unit.

There was a large variation in the number of spatial units used to produce estimates ranging from 1 to 52,000 with median value of 32. 10 studies reported on a single spatial unit ranging in size including islands (Edmondson and Nantucket Data Platform team [2019](#ref-edmondsonMakingItCount2019)), a single administrative region (Fehr & Peers [2014](#ref-fehrpeersNapaCountyTravel2014)), a city (eg. Goldschmidt and Dahl [1976](#Xc732fd1c877ed49ac82863c198b15b359f96233)) and a university campus (Charles-Edwards and Bell [2013](#X721ea84b20e6c1abc2f21010e5775ae0fc71e81)). Studies reporting estimates for larger numbers of units provided estimates at the building level (Ara [2014](#ref-araImpactTemporalPopulation2014)), used high resolution grids (Adamiak, Pitkänen, and Lehtonen [2017](#X1c6c72b80b9275feebacb0744e344ee957ad507)) or administrative areas (McKenzie et al. [2013](#Xe7167b8f9922234a11e6c172cebe4674e0af56f)), often alongside national or large sub-national area coverage. A total of 46 studies did not report the exact number of spatial units for which estimates are produced.

## Temporal units of estimates

The majority of studies (76.0%) report on daytime populations (or both daytime and seasonal) and is reflected in the choice of the temporal units used in the estimates. A total of 34.4% of studies used minutes or hours as their temporal scale, with the second most common unit was split between daytime and night-time estimates (21.9%) or only daytime (14.6%) (Figure 4).

## Estimated population size and composition

There was a large variation in the sizes of estimated populations, ranging from 1 868 to 53,349,074 with median value of 343,956. When the size of dataset was taken into account these figures ranged from 422 to 55,963,096 with median value of 722,000. Combining these two sources of information, largest populations were used or estimated when MP data were used, followed by smaller amount of transport-based studies. Other large studies used various forms of tax data (Figure 5).

In terms of composition, the majority of studies focused on general populations, either total populations present or working populations. That was sometimes extended to capture temporary or seasonal visitors in studies focusing on estimates fo summer resort towns (Erickson [1961](#Xdab9ae9757eb5f474e300a0e4a32b1b00177871); Goldschmidt and Dahl [1976](#Xc732fd1c877ed49ac82863c198b15b359f96233)). The general lack of information on the characteristics of users was often driven not by the theoretical or practical considerations but rather by data availability. For instance many studies based on MP data do not have access to any information on the users (e.g. age, sex, reason for visitation). Some studies sought to capture specific groups of temporary movers including retired individuals undertaken seasonal movements (Happel and Hogan [2002](#Xf2b6ef32229490c6fb183f2e033228e301d52f7); Rose and Kingma [1989](#ref-roseSeasonalMigrationRetired1989)), pupils (Campbell [2010](#X456f982932c9e7187a12c7b51c2354dc03d6563)), , second home users (Adamiak, Pitkänen, and Lehtonen [2017](#X1c6c72b80b9275feebacb0744e344ee957ad507)) or indigenous population (Warchivker, Tjapangati, and Wakerman [2000](#Xae5061268a46a2c7270dac14d859c96c0d7e4a6)), or a on functional area such as university campus (Charles-Edwards and Bell [2013](#X721ea84b20e6c1abc2f21010e5775ae0fc71e81)).

## Reproducibility

60.4% of studies did not report estimates nor indicate where they could be obtained. Similarly, 94.8% of studies did not report on type of software and/or code used to produce them. In some cases, particularly when relatively simple methods were used (for example, equation based), this does not limit reproducibility or replicability of the studies or possibility to implement them in different settings. However, for many studies, particularly those based on proprietary data, the prospects of generating estimates across different areas allied with their validation are limited. More particularly, validation of the results was not common practice with only 36.5% reporting some attempt at validation with lack of data was often quoted as a main reason for not undertaking the task.

# Conclusions

There exists a longstanding interest and demand for temporary population estimates with a growing number of empirical studies that have sought to develop a suite of methods to generate such outputs. However a disconnect arguably exists between the growing prevalence of such studies and the availability of such estimates through statistical agencies wherein their translation into standardised products appears yet to occur. It would seem that this situation may begin to change in the coming years with the emergence of major programs of research focussed on temporary population estimates to include ENhancing ACTivity and population mapping (ENACT) (Batista e Silva et al. 2018) and Pop 24/7 (Martin, et al. 2015). Through these two programs XXX.

Large body of literature on similar topics that have potential overlap such as

* estimates of overall pops (such as WorldPop (Tatem [2017](#ref-tatemWorldPopOpenData2017a)) etc.)
* MP use (without pop est) >> seminal examples like (Calabrese et al. [2006](#ref-calabreseRealTimeRome2006)) and (Silm and Ahas [2010](#X3950f03dfba95d748271b7306184f72c98d5d24))
* SM use (without pop est)
* Twitter (Brogueira, Batista, and Carvalho [2016](#ref-brogueiraUsingGeolocatedTweets2016))
* Snapchat (Juhász and Hochmair [2018](#X0f4ca5bc14f35d17c49b0ed22e90ede33aa156a))
* search engine data (Li et al. [2019](#Xf0d8b901041745d4fb092a57759618e1eee8e81))
* analyses focusing on mobility rather than stocks and flow estimation (Gonzalez, Hidalgo, and Barabasi [2008](#X21243083eb88a5435ea7d3d5019a8d68b6766b3))
* tourism
* tourist arrivals - here some methods could be adapted to TEMPO for instance
* traveler populations at transportation terminals (Jochem et al. [2013](#X61a28b94a7bf9583318ee9f2b19bd7a77a3ea06))
* forecasting tourist volume with search engine data (Li et al. [2018](#ref-liEffectiveTouristVolume2018)), Google Analytics (Gunter and Önder [2016](#ref-gunterForecastingCityArrivals2016)), Google Trends (Önder [2017](#ref-onderForecastingTourismDemand2017))
* crowd estimation and event monitoring
* more classic approach at demonstrations (Yip et al. [2010](#ref-yipEstimationNumberPeople2010))
* agent-based modelling (Chow [2018](#X813bb07c98b7966a30e04a57c14583d9297cfc8))
* social media (Sims et al. [2017](#ref-simsApplicationSocialMedia2017))
* bluetooth (Versichele et al. [2012](#ref-versicheleUseBluetoothAnalysing2012))
* MP (Mamei and Colonna [2016](#X293c3c699139ce600ad357046a8cfacd2f8e975))
* Instagram (Botta, Moat, and Preis [2019](#ref-bottaMeasuringSizeCrowd2019))
* pedestrian movements
* using GPS & MP (Mizzi et al. [2018](#X749b968b5542d74bd35f18cb68730b0b9c8976d))
* using Wi-Fi & Bluetooth (Böhm, Ryeng, and Haugen [2016](#ref-bohmEvaluatingUsageWiFi2016))
* buildings occupancy (Stewart et al. [2017](#ref-stewartCanSocialMedia2017))
* animal & ecology studies
* abundance (Melville and Welsh [2009](#Xfd791eac47869d4ab73b08419f54a1b31e25ede))
* movement (Miller et al. [2019](#ref-millerIntegratedScienceMovement2019))

But many of these studies never move from the analysis of user base to estimates of pop

New data such as SM offer exciting opportunities but bring with them lots of challenges both with data collection and processing (Liao et al. [2018](#ref-liaoBigDataenabledSocial2018):@martiSocialMediaData2018).

Very small amount of studies provide estimates. Mention notable exceptions here… Mention synthetic data…

Very small amount of studies provide code /software used for analyses. Mention notable exceptions here…

Importance of good quality of census and survey data as a basis for other methods.

In the absence of official estimates cities and regions attempt their own calculations (Lamb [1999](#ref-lambEstimatingSeasonalPopulation1999):@monmouthcountyplanningboardSummerCoastalPopulation2008, @fehrpeersNapaCountyTravel2014, @hodurServicePopulationEstimates2015, @edmondsonMakingItCount2019)

## Strengths

* first and only of this kind?
* up to date results
* systematizing state of the art
* offers guidance towards future work (terminology, keywords, themes, etc.)

## Limitations

* fragmented field, lack of standards and definitions, difficult to search; 28.1% of studies included were found outside of main searches
* keywords overlap (ex working pop in epi; seasonal pop in ecology)
* keyword imprecision ex floating population in Chinese lit
* lots of grey lit, for instance 21.9% of studies were in form of various reports we might have missed things

## Recomendations

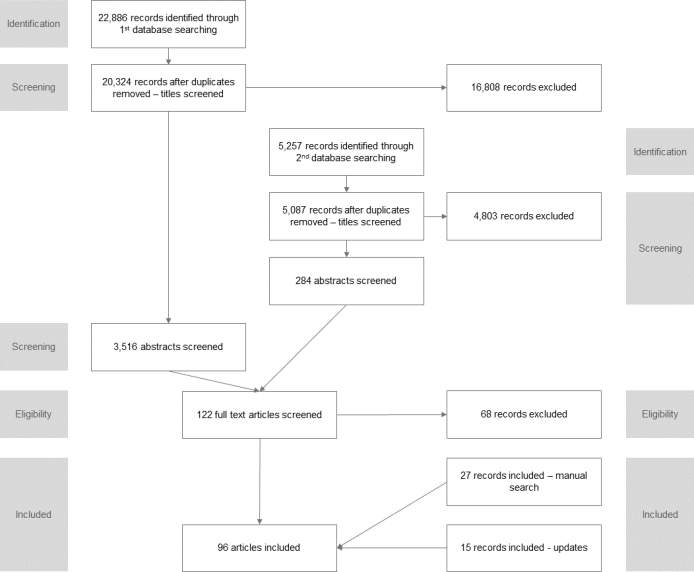
Temporal trends in publication counts indicate that the field is accelerating. 15.6% of studies included were found by monitoring search engine updates. That points to even more urgent need for standardizing and systematizing field.

* guideline for systematic reporting of temporary populations estimates
* using Liao et al. ([2018](#ref-liaoBigDataenabledSocial2018)) life cycle - ideas on each stage of development (collection, compilation, analysis & communication)
* standardization of terminology & keywords
* encourage to share methodology in more detail, preferably with software/code
* encourage to share estimates, if original data not available then synthetic data following methodology

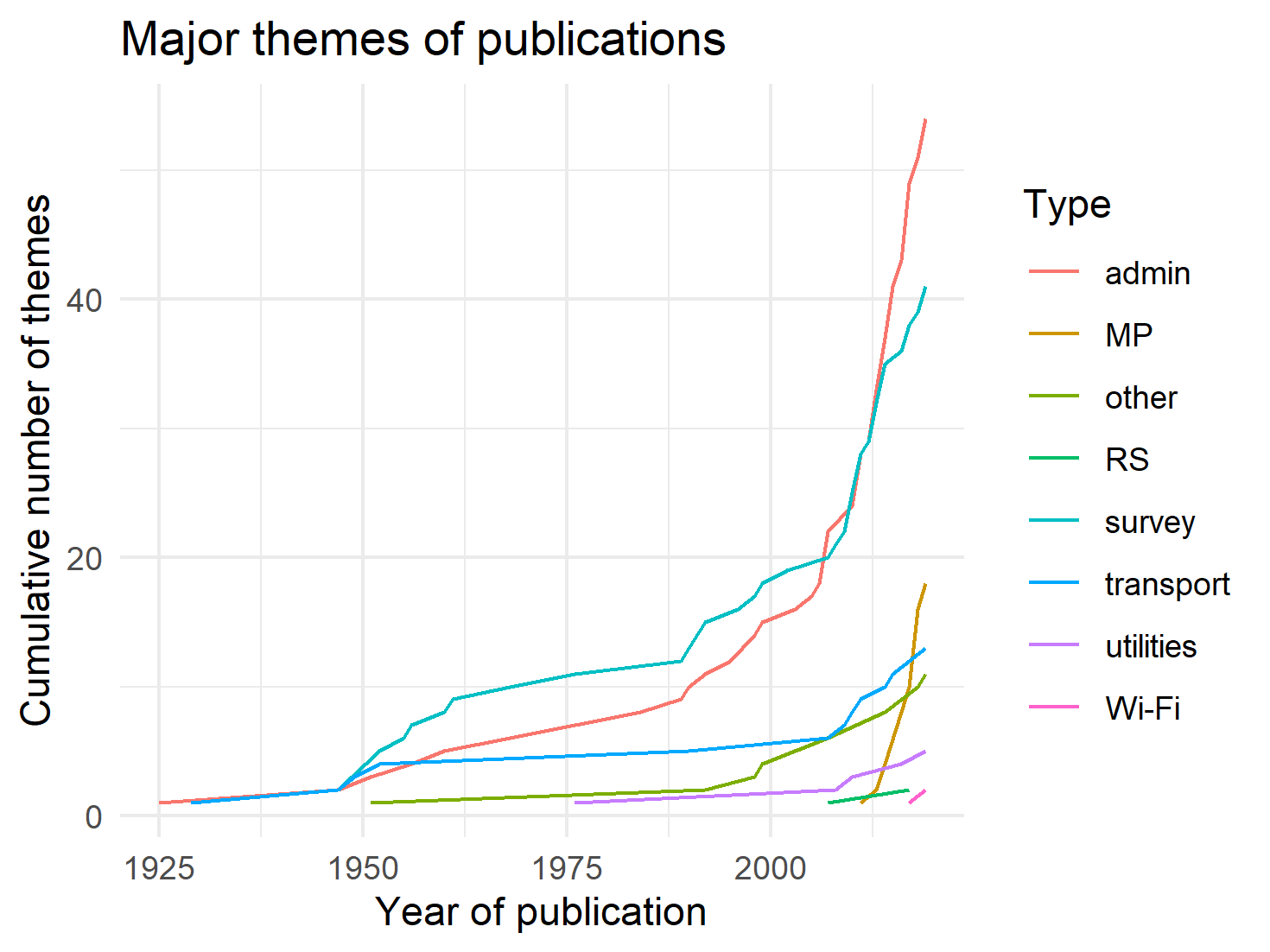
# Contribution

# Figures

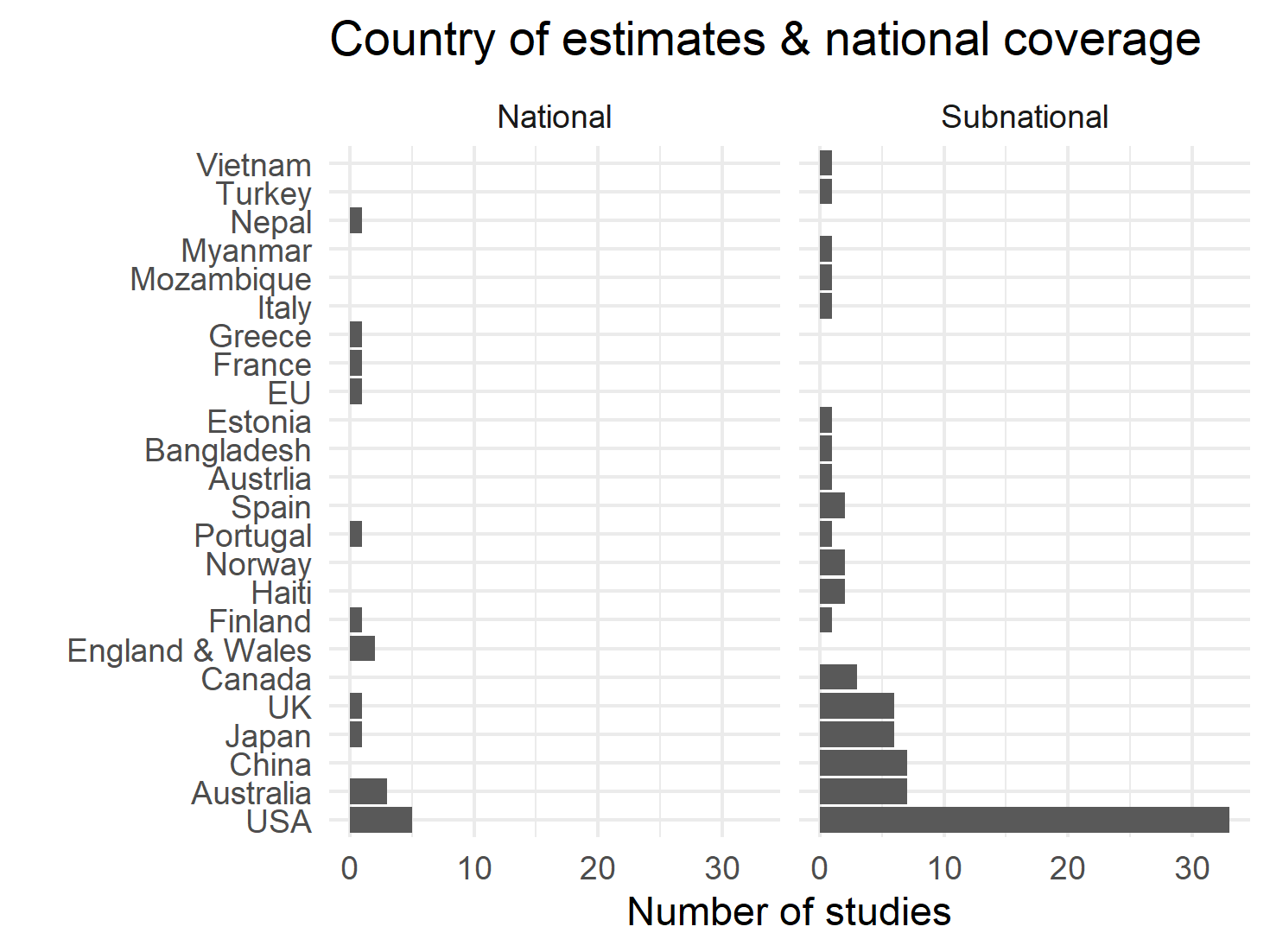
**Figure 1.** Flowchart of study selection.



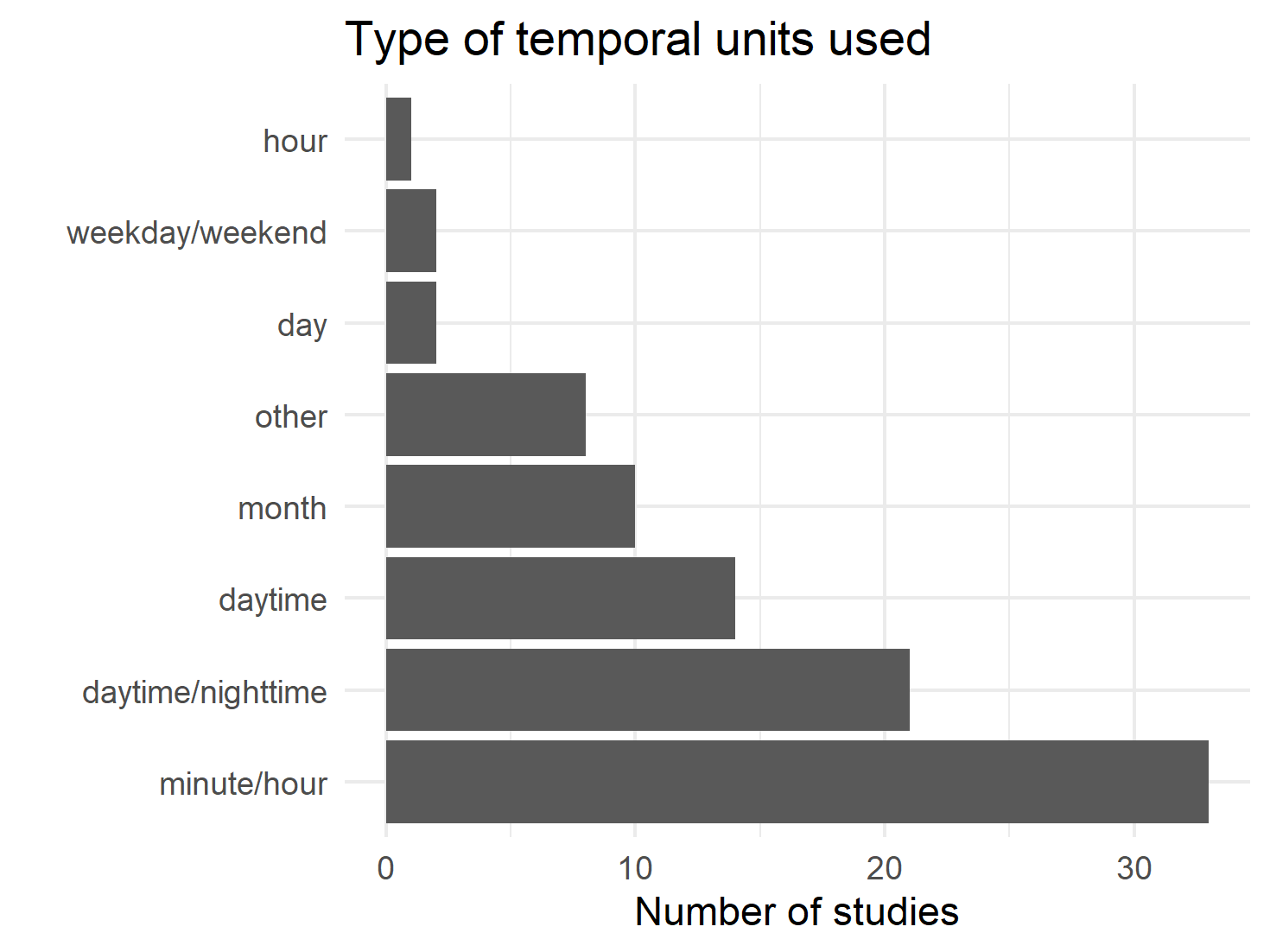
**Figure 2.** Cumulative distribution of year of publication across main themes. Note: Studies can belong to more than one category. ‘Social Media (SM)’ category has been excluded as it only has one member.



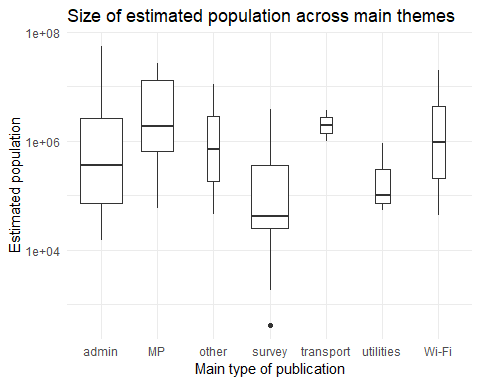
**Figure 3.** Country of temporary population estimates and national coverage. Note: one study describes more than one country.



**Figure 4.** Temporal units used for estimates.



**Figure 4.** Size of population by theme. Note: The Main category used. Box width is proportional to the total number of studies. Studies that did not report on an estimated population size using the size of dataset whenever possible.



# Tables

**Table 1.** Selected characteristics of included studies. Note: \* indicates that study can belong to more than one category.

|  |  |  |  |
| --- | --- | --- | --- |
| Characteristic | Value | n / median | % / min; max |
| Year of publication |  | 2011 | 1925; 2019 |
| Search method | systematic | 54 | 56.25 |
|  | manual | 27 | 28.12 |
|  | update | 15 | 15.62 |
| Type of publication | article | 54 | 56.25 |
|  | report | 21 | 21.88 |
|  | conference | 11 | 11.46 |
|  | thesis | 7 | 7.29 |
|  | chapter | 3 | 3.12 |
| Purpose of publication\* | emergency planning | 22 | 22.92 |
|  | service population | 8 | 8.34 |
|  | other | 7 | 7.3 |
|  | epidemiology | 4 | 4.16 |
|  | commuting | 3 | 3.12 |
| Purpose of publication\* | admin | 54 | 56.24 |
|  | survey | 41 | 42.72 |
|  | MP | 18 | 18.76 |
|  | transport | 13 | 13.56 |
|  | other | 11 | 11.44 |
|  | utilities | 5 | 5.2 |
|  | RS | 2 | 2.08 |
|  | Wi-Fi | 2 | 2.08 |
|  | SM | 1 | 1.04 |
| Study region | single city | 51 | 53.12 |
|  | country | 17 | 17.71 |
|  | admin region | 15 | 15.62 |
|  | multiple cities | 10 | 10.42 |
| Regions for estimates\* | admin | 56 | 58.34 |
|  | grid | 27 | 28.12 |
|  | custom | 7 | 7.3 |
|  | points | 7 | 7.3 |
|  | building | 3 | 3.12 |
|  | Voronoi | 2 | 2.08 |
|  | node | 1 | 1.04 |
| Number of regions for estimates |  | 32 | 1; 52,000 |
| Temporal unit of estimates | minute/hour | 33 | 34.38 |
|  | daytime/nighttime | 21 | 21.88 |
|  | daytime | 14 | 14.58 |
|  | month | 10 | 10.42 |
|  | other | 8 | 8.33 |
|  | day | 2 | 2.08 |
|  | weekday/weekend | 2 | 2.08 |
|  | hour | 1 | 1.04 |
| Size of estimated population |  | 343,956 | 1,868; 53,349,074 |
| Size of dataset |  | 722,000 | 422; 55,963,096 |

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