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Challenges in Geocoding: An Analysis of R Packages and Web Scraping Approaches

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Abstract: Georeferenced data are crucial for addressing societal spatial challenges, as most corporate and governmental information is location-compatible. However, many open-source solutions lack automation in geocoding while ensuring quality. This study evaluates the functionalities of various R packages and their integration with external APIs for converting postal addresses into geographic coordinates. Among the fifteen R methods/packages reviewed, tidygeocoder stands out for its versatility, though discrepancies in processing times and missing values vary by provider. The accuracy was assessed by proximity to original dataset coordinates (Madrid street map) using a sample of 15,000 addresses. The results indicate significant variability in performance: MapQuest was the fastest, ArcGIS the most accurate, and Nominatim had the highest number of missing values. To address these issues, an alternative web scraping methodology is proposed, substantially reducing the error rates and missing values, but raising potential legal concerns. This comparative analysis highlights the strengths and limitations of different geocoding tools, facilitating better integration of geographic information into datasets for researchers and social agents.

Keywords: geocoding; API; web scraping; georeferenced data; open data; data quality

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1. Introduction

In the era of digitalization and connectivity, the use of data is the cornerstone of the technological revolution. Huge amounts of data are generated around the world every second, from financial transactions and health records to social media posts and online purchases [1]. The reduction in the prices of storage systems and technological advances has facilitated the storage, processing, and analysis of this huge amount of data, (potentially) offering a powerful tool for companies, governments, and institutions. However, data alone cannot add value. They must be adequate and of sufficient quality, with a double objective: (i) to facilitate adequate decision-making [2,3]; and (ii) to generate transparency, trust, and knowledge, enabling society to be more efficient [4].

In recent years, initiatives related to offering open data and the reuse of information have increased considerably [5,6]. But having data is not enough. Steps must be taken to ensure the quality and accessibility of the data, as well as the interoperability of the systems used for the data collection, storage, and processing [7]. Clear standards and protocols must, therefore, be established to guarantee the quality of the data and facilitate their use and reuse by the scientific community and other stakeholders [8].

Much of the data that are currently being generated are unstructured data that (may) contain the location of a certain event, obtained from sensors and mobile devices with positioning systems. In contrast, much of the (structured) data available in open data repositories, compatible with spatial information, are not georeferenced. In fact, it is estimated that half of the data openly available do not have geographic information [9], possibly because incorporating the spatial component can be a more complex and costly process than simply collecting information on an object or topic.

The importance of spatial data lies in the data's ability to provide a deeper and more detailed understanding of the world around us [10]. Data are used in a wide variety of applications, from urban planning and transportation to natural disaster management and precision agriculture [11]. Knowing what is happening, and where, is extremely relevant for various social and economic agents, with this being the second category of data most reused and consulted by companies in the EU [12]. For this reason, it is of great interest to the scientific community, and to society in general, to have tools and techniques that make it possible to elaborate/complete/improve datasets with spatial information.

Despite their usefulness, however, spatial data present some common problems and difficulties. One of the biggest challenges is the complexity of data collection and processing. The number and variety of spatial data sources available can be overwhelming, and data processing and analysis can be costly and time consuming. Some of the problems that the researcher usually encounters (when using location data) are related to: (i) missing values; (ii) precision in the coordinates; and (iii) the absence in the metadata of the Coordinate Reference System (CRS) used [13].

The objective of this paper is to propose methods and tools that enable quality datasets to be built/improved that include the spatial component. Specifically, two techniques are proposed to obtain geographic coordinates from postal addresses (geocoding): one based on the use of Application Programming Interfaces (APIs), and another based on the automated extraction of data from websites (web scraping). In both cases, R statistical software [14] is used (version 4.3.2), as this is a free tool widely used in research [15].

2. Related Work

Geocoding, geolocation, or address matching is defined as the action of attributing geographic coordinates (latitude, longitude) to one or more events, using the postal address as a reference [16]. This technique allows researchers and other economic and social agents to carry out analyses and identify patterns based on spatial information. It is a technique that has its uses in multiple areas and fields of research; for example, in: (i) market analysis, where the behavior and trends of various agents can be analyzed according to their geographical location [17]; (ii) tourism, in identifying the behavior patterns of tourists to optimize the offer of certain services [18]; (iii) logistics and transportation, in identifying the locations of distribution centers and facilitating the optimization of routes [19]; (iv) emergency services, to obtain the location of an emergency quickly and accurately [20]; (v) urbanism, in assisting with urban development planning and improving the quality of life of citizens [21]; and (vi) scientific research, in facilitating the study of spatial patterns and the interactions of natural phenomena, as well as carrying out epidemiological analyses [22].

Geocoding has become a widely used technique, both for performing multiple spatial analyses and for decision-making [23]. Various authors refer to geocoding as a powerful tool that enables complex spatial analysis, highlighting the added value that the spatial component brings to datasets. Präger et al. [24] highlight the usefulness of the online geocoding services of Google and OpenStreetMap (OSM) in the detection of factors that promote obesity, concluding that its validity is reasonable, and that it can be used in diabetes surveillance. Chopin and Caneppele [25] use geocoding to carry out an exploratory analysis of mobility between aggressors and victims in crimes of child abuse in France. McIntire et al. [26] geocodes the addresses of 10,750 patients with prostate cancer in the state of Pennsylvania (USA) to create a composite index that identifies the neighborhoods with the highest incidence of the disease. Geocoding also becomes especially relevant in data obtained from social media. Ref. [27] tackled the challenge of geocoding non-geotagged tweets from location-based social networks, proposing a privacy-preserving geocoding method, P-GENT, which ensures privacy while maintaining a high accuracy and utility of the social media data for spatial analysis.

Given the diversity of the geocoding services available, it is crucial to systematically evaluate their output, so as to ensure that decision-makers are relying on the most accurate and reliable data. While some previous work has focused on assessing the accuracy of these services [28,29], there is a need for more in-depth evaluations considering a broader range of current service providers and their evolving technologies. This could lead to a better understanding of their respective strengths and limitations, ultimately enhancing the precision of geocoding applications across different fields.

Due to the growing interest that geocoding is arousing in various economic and social fields, there is now a wide range of methods that address this issue from different perspectives [30–34]. One of the most widely used tools is a web map viewer which, due to its appealing presentation and easy access, allows any citizen to quickly obtain the geographic coordinates of practically any postal address. While there are many options, such as Bing Maps, Here Map, MapQuest, or Waze Map [35], the most used option is Google Maps, with 80% of the market share worldwide [36].

Web map viewers are a perfectly valid option when working with just a few addresses. However, when the goal is to obtain hundreds or thousands of locations, automating the process is essential. Below are two methods that automate the process of obtaining coordinates from postal addresses.

3. Materials and Methods

This section details the systematic approach used to enrich datasets with geospatial information, utilizing various geocoding tools. Our methodology encompasses several steps, starting from the initial data input, through the variable selection and address compilation, to the application of the geocoding processes using different R packages and geocoding service providers. Figure 1 outlines the sequence of operations performed, including decisions on the use of APIs or web scraping based on the effectiveness of the initial geocoding results. Sections 3.1 and 3.2 further elaborate on the specific tools and techniques employed, illustrating our comprehensive approach to ensuring the accuracy and utility of the geospatial data obtained.

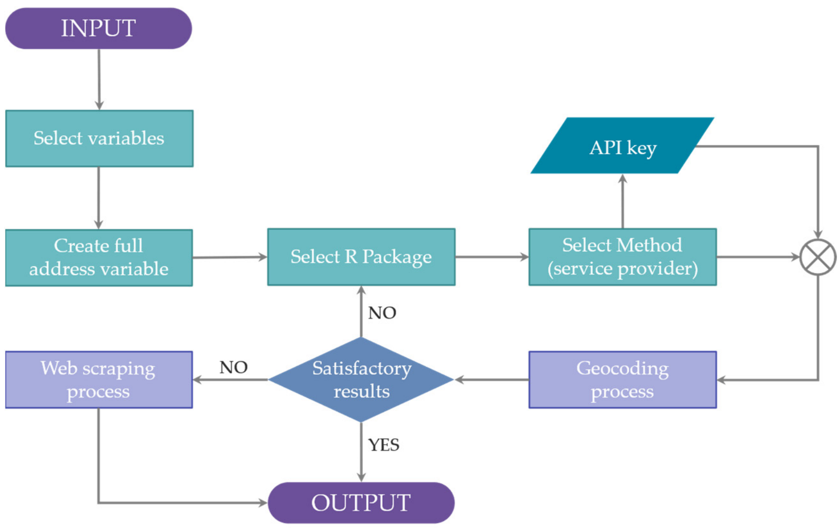


Figure 1. Flowchart of the data enrichment process using geocoding and web scraping techniques.

3.1. Application Programming Interfaces (APIs)

APIs help to significantly smooth out these automation processes, allowing for applications and/or computer systems to be connected with extensive and updated databases of geographic information [37,38]. Some examples of APIs that allow for geocoding processes to be carried out are: (i) Google Maps Geocoding API; (ii) OpenCage Geocoding API; (iii) HERE Geocoding & Search API; (iv) Bing Maps API; (v) Esri ArcGIS REST APIs–Geocoding Services; (vi) Mapbox Geocoding API; (vii) TomTom Geocoding API; (viii) MapQuest Geocoding API; and (ix) Nominatim (free and open source geocoding API using data from OpenStreetMap).

Many of the existing geocoding APIs can be managed using R. This is currently one of the most widely used programming languages in data analysis, and can facilitate massive data collection and subsequent processing. Table 1 shows the correspondence between different geocoding APIs and some R packages that facilitate their use.

Table 1. Correspondence of geocoding APIs and R packages.

Name of API	R Package
Google Maps Geocoding API	ggmap, tidygeocoder, googleway, RgoogleMaps
Bing Maps API	tidygeocoder
HERE Geocoding & Search API	hereR, tidygeocoder, nominatimlite
MapQuest Geocoding API	mapquestr, tidygeocoder, nominatimlite
Nominatim API	osmar, tidygeocoder, ggspatial, osmdata, nominatimlite, tmaptools
OpenCage Geocoding API	opencage, tidygeocoder, nominatimlite
Mapbox Geocoding API	tidygeocoder
TomTom Geocoding API	tidygeocoder
ArcGIS REST API-Geocoding Services	arcgisbinding, tidygeocoder

Two of the most prominent R packages shown in Table 1 are ggmap [39] and tidygeocoder [40]; the first for being the one that was downloaded the most times from the CRAN repository during 2023 (see Table 2), and the second for offering great versatility, since it can work with all of the aforementioned APIs.

Table 2. The number of times each R package was downloaded from the CRAN repository during 2023. Source: compiled by the authors, based on the results reported by the cranlogs R package.

R Package	Number of Downloads
ggmap	724,324
RgoogleMaps	286,308
tmaptools	187,888
ggspatial	115,003
osmdata	89,737
tidygeocoder	42,605
googleway	42,265
nominatimlite	7798
mapboxapi	7724
hereR	7494
opencage	4061
osmar	1267

While APIs simplify the process of geocoding, every provider sets specific limitations on the utilization of their service without incurring costs. For instance, accessing the Google, Bing, or HERE APIs requires users to first register and acquire a personal key (API-KEY). Table 3 presents the various features and conditions for the free use of each API, detailing the requirements and the extent of the free access provided by these platforms.

Since there are different options (R packages) that enable geocoding processes to be carried out, a comparison of their effectiveness would be useful. To do this, we use a large dataset (the street map of Madrid), which contains more than two hundred thousand observations (postal addresses) and 20 variables [41]. These variables include road type (VIA_CLASE), street name (VIA_NOMBRE, VIA_NOMBRE_ACENTOS), house number (NUMERO), type of numbering (TIPO_NDP), and unique identifiers for the road (COD_VIA) and house number (COD_NDP). Additionally, the dataset comprises the district (DISTRITO) and neighborhood codes (BARRIO), postal codes (COD_POSTAL), and geographical coordinates in both the ED50 (UTMX_ED, UTMY_ED) and ETRS89 (UTMX_ETRS, UTMY_ETRS, LATITUD, LONGITUD) geodetic systems. It also includes the angle of the house number signage relative to the building facade (ANGULO_ROTULACION).

Table 3. Characteristics and conditions of use of different geocoding APIs.

Name of API	API-KEY Needed	Conditions of Use
Google Maps Geocoding API	YES	Credit of USD 200 per month (equivalent to 28,500 requests). *
Bing Maps API	YES	50,000 requests per day for educational/non-commercial uses.
HERE Geocoding & Search API	YES	1000 free requests per day.
MapQuest Geocoding API	YES	15,000 free transactions per month.
Nominatim API	NO	
OpenCage Geocoding API	YES	2500 free requests per day (for testing purposes).
Mapbox Geocoding API	YES	100,000 free requests per month. *
TomTom Geocoding API	YES	2500 free requests per day.
ArcGIS REST API-Geocoding Services	NO	

* Bank details must be entered into the registration platform.

This dataset enables two actions to be completed: (i) obtaining coordinates from postal addresses; and (ii) determining the geographic distances between the coordinates obtained in the geocoding process and those provided in the dataset itself. A random sample (n = 15,000) of postal addresses is selected, and the different R packages under analysis in this paper are tested. Given the usage limitations outlined in Table 3, the sample is divided into 100 subsamples (S1 to S100) of 150 observations each.

The versatility of the tidygeocoder R package is scrutinized, emphasizing its support for up to 13 different geocoding services. Nine methods (service providers) have been selected, applying this function across 150 subsamples. The geocoding process is conducted using the package's geo() function, showcasing its extensive capabilities. Similarly, six alternative R packages are analyzed, each with a function developed to geocode using a single service provider: (i) ggmap [42] for Google Maps Geocoding API; (ii) hereR [43] for HERE Geocoding & Search API; (iii) mapquestr [44] for MapQuest Geocoding API; (iv) tmaptools [45]; (v) opencage [46]; and (vi) mapboxapi [47] for the Mapbox Geocoding API. All tests were conducted using the same computer, with the following specifications: 3.30 GHz processor speed and 8 GB of RAM.

Knowing the speed of the process (computation time) and the success/error rate (number of missing values) for each package and method (service provider) allows the researcher to select the appropriate option for the task in hand. However, this is not enough; the reliability of the data is also a fundamental characteristic. For this reason, we consider it appropriate to audit the results obtained, calculating the Euclidean distance between the coordinates obtained in the geocoding process and the coordinates included in the dataset used, implementing the st_distance() function of the sf package [48]. This verification process, in addition to providing confidence to the end user, fulfils one of the purposes of this document: to generate (sets of) quality data.

3.2. Automated Data Extraction from Websites (Web Scraping)

The use of R packages that interact with geolocation service APIs has proven to be an efficient option for geocoding postal addresses and obtaining geographic coordinates quickly. However, in some cases, the results are seen to be unreliable, which gives rise to the need to explore other alternatives. One such alternative is the promising strategy of web scraping on web map viewers. This technique offers the possibility of extracting geographic information directly from online platforms, which expands the data sources available for geocoding. Also, by getting data directly from map viewers, dependency on third-party geolocation service providers can be reduced, which helps increase autonomy in the geocoding process. In this section we explore in detail the use of web scraping as a valuable tool for obtaining coordinates from postal addresses, offering a reliable and complementary alternative to the methods presented in the previous section.

The widespread use of the Internet, together with different platforms, both private and open source, allows any agent to locate a specific postal address on the map and, consequently, to obtain its geographic coordinates. Online map viewers, such as Google Maps, have become very popular and useful tools nowadays, due to their appealing presentation, easy access, and the large amount of geographic information they provide. In addition to Google Maps, there are other options, such as Bing Maps, HERE WeGo, OpenStreetMap, and many others, each with their own interface, but with a similar appearance. These map viewers allow users to locate postal addresses, explore remote locations around the world, and plan routes. They also make it possible to search for and obtain geographic coordinates from postal addresses. However, as we mentioned at the beginning of the paper, this process carried out manually fulfils its objective for specific enquiries, but it is not efficient when multiple coordinates are needed.

A possible solution to this problem is to use web scraping techniques, which enable information to be extracted from web pages, their HTML code scanned, and data extraction patterns generated [49]. These techniques can be implemented in R with the rvest [50] and RSelenium [51] R packages, among others, although there are notable differences between them. On the one hand, rvest enables the extraction of data from web pages through static web scraping; that is, selecting elements of a web page using CSS and XPath selectors [52]. On the other hand, with RSelenium, the user can connect with web pages that require interaction to extract data. RSelenium uses a Selenium server [53] to control a web browser and perform tasks, such as clicking buttons, filling in forms, or browsing different pages. In this way, data can be extracted from web pages that require interaction.

The proposed method consists of automating the sequential scheme, represented in Figure 2, by implementing various functions of the RSelenium package. To verify the operation of this procedure, and purely for academic purposes, we develop an R script that allows the described sequence to be carried out (see the Supplementary Materials).

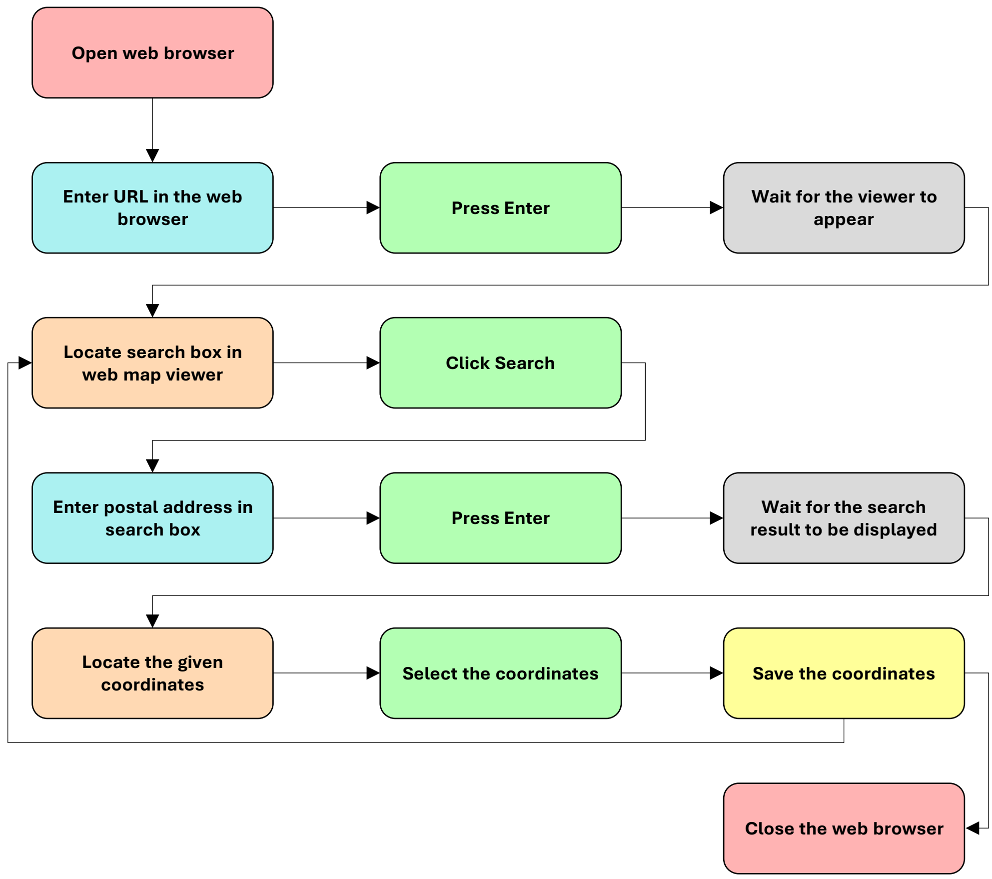


Figure 2. Sequential diagram of the manual retrieval process to obtain coordinates from a web map viewer.

When using web scraping techniques, it is essential to include pauses in the script, allowing the browser to perform certain actions, such as opening pages and loading content, before continuing. When defining a sequential system, in which the user must wait until one step is finished to start the next, several issues must be considered, such as the need for a certain web page to be fully loaded before interacting with its content. In fact, since this procedure is based on interacting with specific elements of the web, such as clicking buttons or filling in forms, the possible limitations of the equipment/computer system used (internet connection speed, etc.) should also be considered.

4. Results

This section presents the results obtained from applying the methodology outlined in the previous section. Following the procedures and analyses described, we have systematically evaluated the performance, accuracy, and limitations of various geocoding services. The outcomes of these evaluations, including computational times, the incidence of missing values, and overall efficiency of each method, are detailed in this part of the paper. The results are crucial for understanding the practical implications of choosing one geocoding service over another, as they provide concrete data on performance metrics and reliability across different platforms.

Table 4 shows the computing times for the subsample and method (service provider) used, as well as the missing values (number of non-geocoded addresses, from here on NA). As can be seen, MapQuest is the fastest method, with an average of 2.099 s per subsample (314.86 s for the 15,000 observations), while the slowest methods are OSM and OpenCage, with a computation time of 139.641 and 104.805 s per subsample, respectively. Regarding missing values, OSM is the method with the highest error rate, at 3.1% (466 NAs), followed by HERE, with 0.95% (142 NAs).

Table 4. Time and number of NAs (in brackets) using tidygeocoder R package.

Method	S1	S2	S3	S98	S99	S100	Average * (S1 to S100)
Google	16.399 (0)	14.927 (0)	14.161 (0)	13.309 (0)	11.689 (0)	13.055 (0)	15.172 (0)
Bing	34.862 (0)	41.397 (0)	34.254 (0)	45.591 (0)	47.16 (0)	46.922 (0)	39.658 (0.007)
HERE	22.591 (0)	21.751 (1)	22.067 (0)	21.888 (0)	21.799 (2)	21.905 (0)	22.08 (0.947)
MapQuest	2.095 (0)	1.966 (0)	2.002 (0)	1.992 (0)	1.903 (0)	2.053 (0)	2.099 (0)
OSM	103.15 (3)	105.852 (3)	106.63 (7)	153.322 (1)	243.697 (1)	176.853 (4)	139.641 (3.107)
OpenCage	102.294 (0)	102.24 (0)	102.413 (0)	102.121 (0)	102.385 (0)	102.24 (0)	104.805 (0)
Mapbox	16.286 (0)	19.577 (0)	18.654 (0)	17.618 (0)	18.15 (0)	20.239 (0)	20.968 (0)
TomTom	19.125 (0)	19.485 (0)	18.885 (0)	19.107 (0)	19.677 (0)	18.981 (0)	19.894 (0.007)
ArcGIS	48.599 (0)	53.701 (0)	54.623 (0)	50.831 (0)	49.717 (0)	51.08 (0)	50.785 (0)

* All results in the Supplementary Materials.

Complementing the previous information, we analyze other R packages that enable geocoding by implementing some of the methods presented in the first column of Table 4. The ggmap and hereR packages present results like those obtained with the "Google" and "HERE" methods of tidygeocoder. In the case of the mapquestr package, the computation times are much higher than those obtained with the "MapQuest" method. The method tmaptools halves the computation times of the "OSM" method, but maintains the same number of missing values (NA). The opencage package reports computation times higher than those obtained by the "OpenCage" method. The opposite occurs with the mapboxapi package, which reduces the computing times of the Mapbox service used in tidygeocoder by more than 60% (see Table 5).

Table 5. Time and number of NAs (in brackets) using different R packages.

R Package	S1	S2	S3	S98	S99	S100	Average * (S1 to S100)
ggmap	12.284 (0)	17.146 (0)	15.662 (0)	15.64 (0)	16.008 (0)	15.369 (0)	16.706 (0)
hereR	26.773 (0)	24.621 (0)	24.395 (0)	24.472 (0)	25.554 (0)	26.036 (0)	24.743 (0)
mapquestr	26.432 (0)	26.001 (0)	27.406 (0)	27.417 (0)	27.412 (0)	27.031 (0)	27.169 (0)
tmaptools	59.07 (3)	57.651 (3)	57.134 (7)	54.086 (1)	56.773 (1)	54.241 (4)	57.908 (3.053)
opencage	128.102 (0)	130.952 (0)	123.679 (0)	124.793 (0)	125.149 (0)	124.511 (0)	131.743 (0)
mapboxapi	7.25 (0)	18.988 (0)	18.333 (0)	16.164 (0)	15.829 (0)	16.144 (0)	16.335 (0)

* All results in the Supplementary Materials.

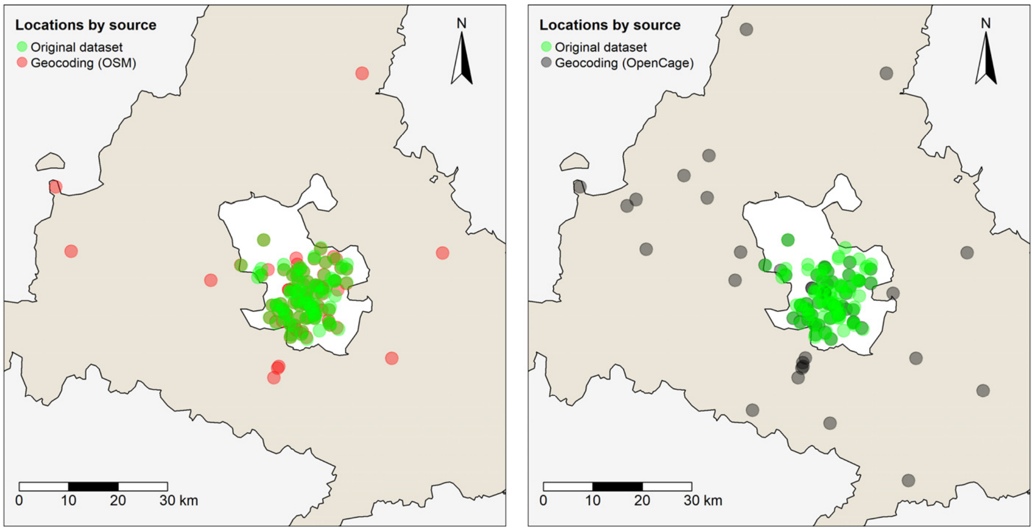
To audit the results obtained, we have compared geocoded coordinates with the original data. Table 6 shows the median of the Euclidean distances obtained for each subsample analyzed and for each of the 15 methods used (M1–M15). The median is used instead of the average, to avoid the distortions produced by the extreme values caused by geocoding errors that report greater distances with respect to the coordinates offered in the original dataset. M9 is the method that best replicates the coordinates provided in the Madrid street map. The M3, M11 and M12 methods also offer results with a high degree of accuracy, giving an average distance within less than 2 m.

Table 6. Median of the Euclidean distance, in meters, between the coordinates included in the original dataset and those obtained by geocoding for each subsample and method.

	Method	S1	S2	S3	S98	S99	S100	Average * (S1 to S100)
M1	Google **	6.6925	6.779	7.985	5.2305	8.453	7.771	6.5186
M2	Bing **	4.9065	6.0135	6.3115	5.487	5.2745	4.7655	5.2322
M3	HERE **	1.7485	1.775	1.7635	1.756	1.7815	1.92	1.7739
M4	MapQuest **	9.5625	8.6115	9.7975	9.628	8.932	9.8735	9.6415
M5	OSM **	65.413	56.843	91.327	60.341	74.502	83.3505	71.2541
M6	OpenCage **	461.807	264.147	1286.724	270.0545	709.77	242.6665	483.547
M7	Mapbox **	9.711	8.1825	15.6265	9.4355	9.896	15.297	10.6494
M8	TomTom **	6.8475	6.46	7.1395	5.4055	5.53	5.6115	5.7818
M9	ArcGIS **	0.003	0.002	0.003	0.002	0.003	0.002	0.0025
M10	ggmap	6.502	6.967	7.985	5.2305	8.453	7.771	6.5124
M11	hereR	1.7485	1.775	1.7635	1.756	1.767	1.92	1.7744
M12	mapquestr	1.7485	1.7845	1.7635	1.756	1.829	1.92	1.7957
M13	tmaptools	79.43	65.845	79.323	61.588	75.837	87.4775	70.0706
M14	opencage	466.58	264.147	1286.724	270.0545	686.682	242.6665	481.9236
M15	mapboxapi	9.711	8.335	15.468	9.4355	9.896	15.297	10.6473

* All results in the Supplementary Materials. ** Method from the tidygeocoder R package.

Based on the distance between the coordinates obtained by geocoding and the coordinates included in the original dataset, the methods M5, M6, M13 and M14 are seen to be the ones that return the greatest discrepancies in distances. This is mainly due to detection/interpretation errors by the municipality. For example, for the first subsample (S1), the methods M5 and M13 (Nominatim service), in addition to not geocoding three postal addresses (see Tables 4 and 5), impute ten locations to municipalities other than Madrid (see the red dots on the left panel of Figure 3). Of these ten points, nine are located in towns close to the Spanish capital, within the Community of Madrid itself (lightly brown-colored area), while another point is located in the American continent, specifically in Mexico City. Similar errors occur with the M6 and M14 (OpenCage) methods. In this case, all of the postal addresses of S1 are geocoded, but the results are not as accurate as one would hope (see the black dots in the right panel of Figure 3). Twenty-five locations are outside the municipal boundaries of Madrid, two of which are positioned again in Mexico City. The green dots indicate the coordinates offered in the original dataset, corresponding to the 150 postal addresses in the subsample.



(**a**) (**b**)

Figure 3. Graphic representation of the geographic coordinates corresponding to the postal addresses of the S1 subsample: (**a**) coordinates obtained by geocoding (methods M5 and M13) are in red; (**b**) coordinates obtained with the M6 and M14 methods are in black. Coordinates included in the original dataset are shown in green (both panels). In brown, the Autonomous Community of Madrid; in white, the Municipality of Madrid.

Regarding the use of web scraping techniques, the following results have been obtained. On the one hand, in terms of accuracy and missing values, the proposed method matches the performance of APIs, as it can retrieve the same coordinates reported by the R packages explored in this document. On the other hand, as expected, the time taken to obtain the coordinates is substantially longer than that reported by the R packages, largely due to the waiting times that must be introduced into the algorithm to allow the browser to load the necessary data. Despite this, this method significantly reduces the time and effort required to manually collect geographical data.

5. Discussion and Conclusions

In a world where georeferenced data offers substantial added value, most freely available databases lack spatial information. This study provides a comparative analysis of geocoding techniques to address this gap, focusing on API management through R packages and web scraping methods. Our findings highlight the significant variability in performance across different methods.

We evaluated fifteen geocoding methods using tidygeocoder and other R packages, noting computation times, missing values, and accuracy relative to the original dataset coordinates. Key outcomes include: (i) computation time: MapQuest emerged as the fastest method, averaging 2.099 s per subsample, significantly quicker than others like OSM and OpenCage, which took over 100 s; (ii) missing values: Nominatim (OSM) had the highest error rate, with an average of 3.107% missing values per subsample, while most methods, including Google and Bing, had negligible missing values; (iii) accuracy: ArcGIS was the most accurate, with an average Euclidean distance of 0.0025 m from the original coordinates, outperforming others like OpenCage, which had an average error of 483.547 m.

The results equip researchers and social agents with insights to select the most suitable geocoding method based on their needs. The significant outcome of this study is the identification of MapQuest as the fastest tool, ArcGIS as the most accurate, and the caution against using Nominatim for high-precision tasks due to its higher error rates.

Web scraping techniques were proposed as an alternative, demonstrating reduced error rates and missing values compared to some API-based methods. However, this approach raises potential legal and ethical concerns, and requires adaptation to specific platforms.

Future research could develop an R package to automate the geocoding method selection based on specific criteria, potentially integrating machine learning techniques to predict the methods' performance. This advancement would further enhance the integration of spatial data into existing and new databases, offering substantial economic and social benefits.

By providing a detailed comparative analysis, this research aids in making informed decisions about geocoding approaches, ultimately facilitating better integration of geographic information into datasets across various research settings needs.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/ijgi13060170/s1, Table S1: Time and number of NAs using tidygeocoder R package; Table S2: Time and number of NAs using different R packages; Table S3: Median of the Euclidean distance, in meters, between the coordinates included in the original dataset and those obtained by geocoding for each subsample and method; File S4: Web scraping R script.

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