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A critical review on the key issues and optimization of agricultural residue transportation

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ABSTRACT

In recent years, residue-to-energy utilization has become an important energy source that can alleviate the reliability of fossil fuel, and agricultural residue (AR) transportation has great potential for optimization in the AR supply chain. However, various methods presented make their correct implementation difficult for sustainable optimization. Therefore, four key issues of the AR transportation for bioenergy production have been thoroughly reviewed: (i) distribution of AR in cropland, (ii) estimation of transportation distance, (iii) variability of vehicle arrangements, and (iv) (de)centralized transportation patterns. This review has several findings. To begin with, land cover classification method with remote sensing technology is suggested to locate the distribution of AR, thereby being helpful for facilitates decision-making optimization. Second, electronic navigator applications (Google Maps or Baidu Maps) are recommended for transportation distance estimation, and the implementation of manipulating Baidu Maps with R is provided. Third, the vehicle selection bias would bring estimation gaps, so a vehicle database is required to satisfy the local needs. And finally, transportation distance, the requirement of AR pretreatments and brokers' participation can affect the decision of (de)centralized transportation patterns. The findings and technical details discussed are especially useful for researchers and bioenergy project investors who intend to reduce the AR transportation cost in the future, especially for developing counties.

1. Introduction

Agricultural residue (AR) is an important by-product of agricultural production [1]. With the booming increase of global crop yield, the amount of AR is also rising. According to the figure from FAO, the world's grain (rice, wheat, corn) yield was 2664 million tons in 2018, and this generated approximately 6563 million tons of grain residue (see Fig. 1). Although residue incorporation can be beneficial for soil fertility improvement and crop yield increase, the amount of residue that can be consumed by soil is finite. On the other hand, with the rising concerns of air pollution and environmental protection, residue open burning is no longer allowed in most regions. Also, energy scarcity is seriously affected economic growth and people's living standard. So, to turn the surplus of AR to fortune can be very attractive. By considering the chemical and physical properties [2], plenty of researches have been carried out to assess the potential of suitable amount of AR for bioenergy proposes from either international or regional scope. Based on the average of global AR production between 1997 and 2001, Kim and Dale (2004) [3] assessed that the global potential of bioethanol production from AR was 442 GL yearly, which could substitute 353 GL petrol (was equal to 32% global petrol consumption). By calculating Net Primary Productivity between 2000 and 2014, Tum et al. (2016) [4] inferred that global AR bioenergy potential was 35.9 EJ yearly. Bentsen et al. (2014) [5] conducted a nationwide analysis on AR production (averages over 2006–2008), and estimation revealed that theoretical energy potential was 65 EJ yearly, which could account for 15% of the world's primary energy consumption. On the national scale, Jiang et al. (2012) [6] estimated that AR could provide 7.4 EJ bioenergy yearly, representing 8.27% of the total energy consumption of China in 2009. Li et al. (2012) [7] estimated that China's AR could generate 1.75×10^5 GWh of electric power and 43 million tons of bioethanol in 2008. Qiu et al. (2014) [8] calculated that the amount of AR for bioenergy business was 73.5–120.5 million tons of standard coal equivalent, which accounted for 2.5–3.8 China's total energy consumption in 2012. Muth et al. (2013) [9]

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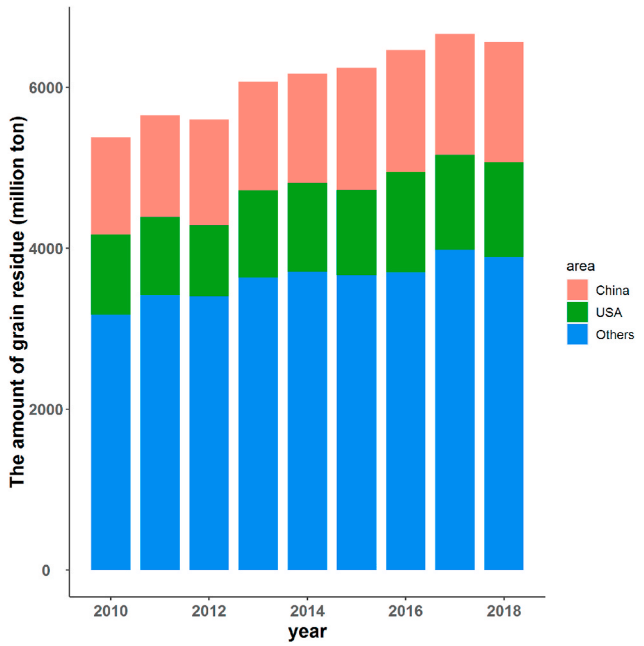

Fig. 1. Estimation of global grain (corn, rice, wheat) residue production. Other areas represent the world that excluded China and the USA. Data are based on FAO grain production between 2000 and 2018 [11]. AR production is estimated by equation: R = G × r, where R is the AR production of the crop; G is grain production based on FAOSTAT data; r is residue/grain ratio, based on Bentsen et al. (2014) [5].

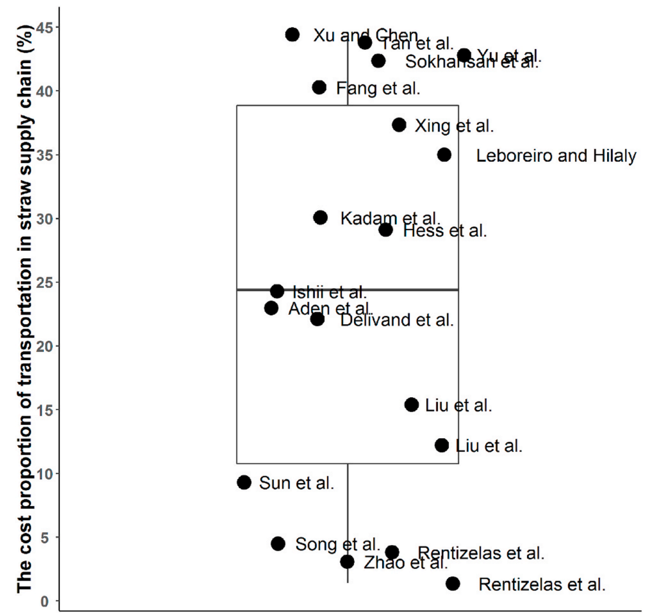

Fig. 2. The boxplot of cost proportion of transportation in AR supply chain. The parameters are captured from Refs. [12–30].

predicted that since 2030, over 207 million tons of AR would be used for bioenergy, and such resources could produce 68 billion liters of biofuels in USA. The evaluation showed that AR resource had the potential of generating 16.25 GW power in India between 2008 and 2009 [10].

Now, bioenergy technologies are becoming more and more mature, but reducing the cost in AR supply chain is another challenge. Because AR has the features of widespread in the field and seasonal restrictions of collection, AR supply is highly influenced by agricultural production, which makes its supply chain significantly different from conventional fossil fuel supply. AR supply chain mainly consists of three main activities, collection, transportation and storage [12–14]. On average, transportation cost accounted for one-fourth of the total AR supply cost (see Fig. 2). Taking a concrete example of AR transportation in China, unit transportation costs were significantly different among studies. With the latest published articles and longer transportation distance, unit transportation costs were increasing and decreasing respectively (see Fig. 3(a), Fig. 3(b)). Therefore, for the purpose of designing an optimized AR supply chain, transportation activity should not be simplified by borrowing transportation fee rates from other researches, and it has great potential for efficiency improvement.

Considering the importance of transportation in the bioenergy utilization, an extensive body of review would be expected in this area. However, while the review is available on the overall biomass supply chain [47–50] or biomass transportation [51,52], few reviews have concentrated on the AR transportation perspective. Azevedo et al. (2019) [53] reviewed the supply chain performance of renewable energy with a bibliometric approach, and they found out that the optimization of transportation cost is an inevitable problem in all the most-cited articles. Among the existing literature about AR supply chains, the methods for estimating transportation are also changing dramatically. Inevitably, GIS, logistics planning, traffic engineering and other related knowledge will be required, and these methods present a general tendency from simple to complicated, with the powerful data-driven accessibility and multidisciplinary cooperation. For example, remote sensing techniques with high-resolution satellite images can help orient the cropland location more precisely; online-electronic navigator applications can be used to design a more realistic travelling route. If the supply cost can be controlled and further compressed, in energy production sector, using AR as feedstock could be remarkably cheaper than using coal [33]. Therefore, the present review emphasizes on providing researchers and bioenergy project investors who intend to reduce the AR transportation cost with cogent answers concerning the following key issues:

- How to allocate AR resource (intensity) inside cropland?
- How to calculate transportation distance?
- How to choose the vehicle in AR transportation?
- What are the concerned factors that influence the (de)centralized transportation patterns?

This review is organized as follows. Section 2 describes bibliometric analysis for search result records in AR supply chain; section 3 reviews the existed allocation methods of AR resource inside collectable area; section 4 reviews on different methods for AR transportation; section 5 and 6 presents the discussion of variability of vehicle arrangements and (de)centralized transportation patters; and in section 7 the main conclusions and future perspective are drawn.

2. Material and methods

The literature used in this review is collected from the web of science database for the period 2000–2019. Also, apart from English articles, publications in Chinese (collected from CNKI database) are included in this review, but do not incorporate into the bibliometric analysis. Bibliometric analysis is applied to figure out the tendency of publications and most relevant sources (journals) on the AR supply chain. The bibliometric works for this review are entirely based on the statistical software R and R package “bibliometrix” [54], which are useful to manipulate bibliometric data, text processing and graphical visualization. The different synonyms of keywords are considered, in order to avoid the neglect of related publications. For example, AR can be paraphrased as crop residue or straw, and supply can be paraphrased as logistics, delivery or transportation. Hence, 12 different combinations of search strategies are performed to retrieve these keywords to be present with the search fields (title, abstract, keywords) in every literature.

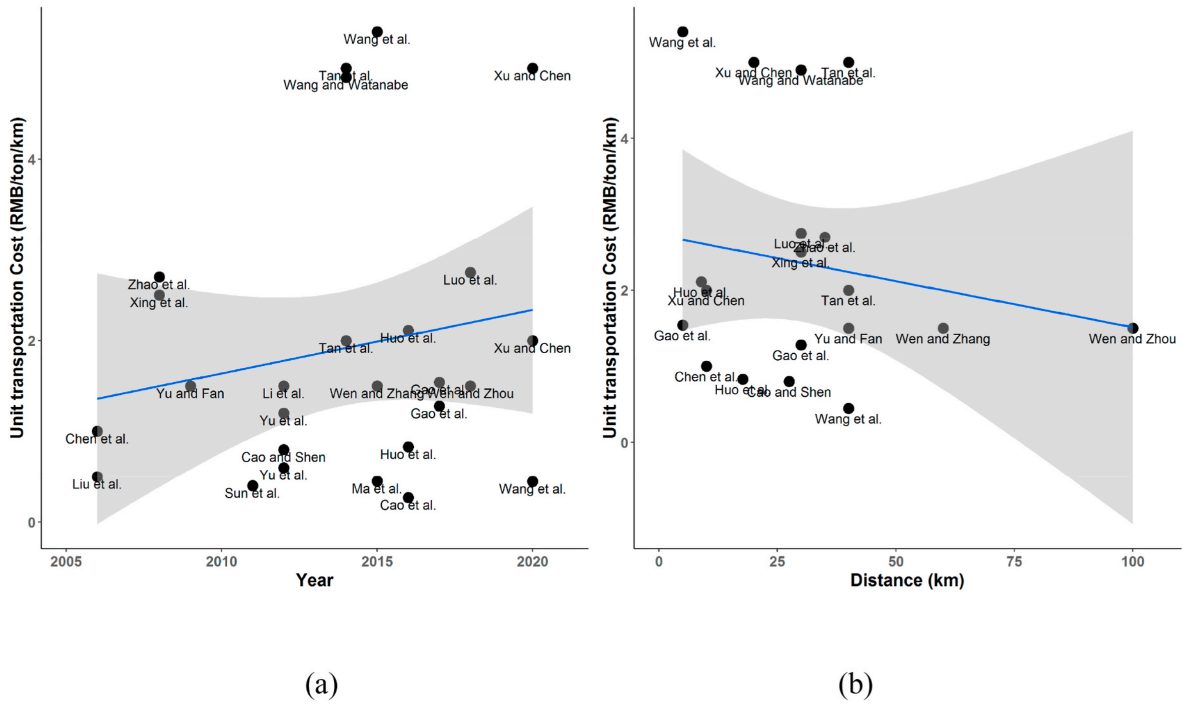

Fig. 3. (a) The unit cost of AR transportation sorted by year, and (b) the unit cost of AR transportation sorted by distance. The parameters are captured from Refs. [7,15,17,27,28,31–46].

Furthermore, to eliminate duplicate search results and to concentrate the researches on AR supply chain, duplicate removal and research area filtering of publications are conducted simultaneously via R. The roadmap of the literature search strategy and data cleaning process is shown in Fig. 4. The research on AR supply (delivery/logistics) system has been a popular topic of raising interest in the publications, as Fig. 5 shows. It can be observed a significant rising trend since 2006. Fig. 6 reveals that the journal with the most publications on AR supply chain was Biomass and Bioenergy, followed by the Renewable and Sustainable Energy Review. Content analysis is used for finding productive countries based on authors' address. The spatial distribution of publications reveals that Chinese research institutes have the most enthusiasm for studying AR supply chain, followed by the USA and Canada (see Fig. 7).

3. Distribution of AR in cropland

The characteristics of the scattered distribution of AR in cropland should be taken into consideration. Nearly all researches applied to case studies of AR supply inside an administrative boundary [55–57], and a significant share of area (buildings, mountain and water) [58] cannot be regarded as an AR production area. So, land cover classification is necessary to distinguish the collectable area, and AR should only be allocated to these areas. In other words, the intensity of AR distribution is irregular. However, simple assumptions of AR distribution were made in some of the researches. Singh et al. (2011) [59], Chiu et al. (2016) [60] and Sun et al. (2017) [14] assumed that AR was evenly distributed in the study area. Uniformly spatial distribution of AR may cause underestimation of allocation intensity. For instance, if cropland is concentrated on a specific area and the location of bioenergy factories are closed to cropland, uniform distribution will exaggerate transportation distance and distort the cost of transportation.

The use of land cover dataset can significantly promote the accuracy of AR distribution. Nie et al. (2020) [61] assessed the technical potential of bioenergy schemes in China with crop growth models and GIS. Land cover dataset came from Data Center for Resources and Environmental Sciences, the Chinese Academy of Sciences http://www.resdc.cn was used to identify the cropland from the field, and thereby estimating the intensity of AR resource. To estimate the EU bioenergy potential from AR, European land cover raster data are an important source for building up geographical layers for cropland [62,63].

With the rapid progress and development of remote sensing technology, instead of vague assumption of uniform distribution of AR resource in cropland or downloading the existed land cover data, using high-resolution satellite imagery directly for land use classification can

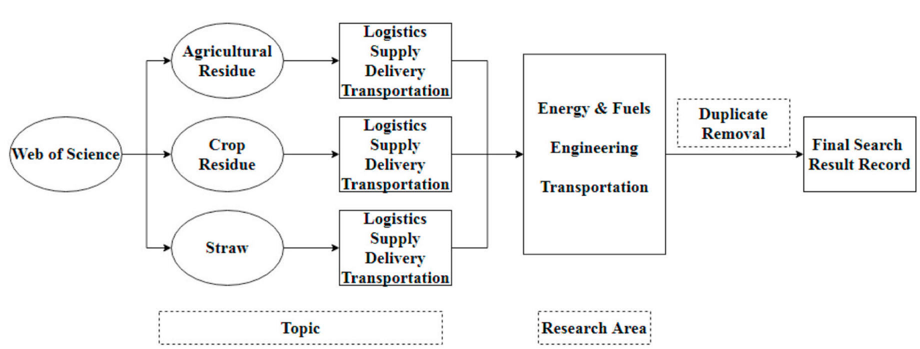

Fig. 4. The roadmap of literature searches strategy and data cleaning processes.

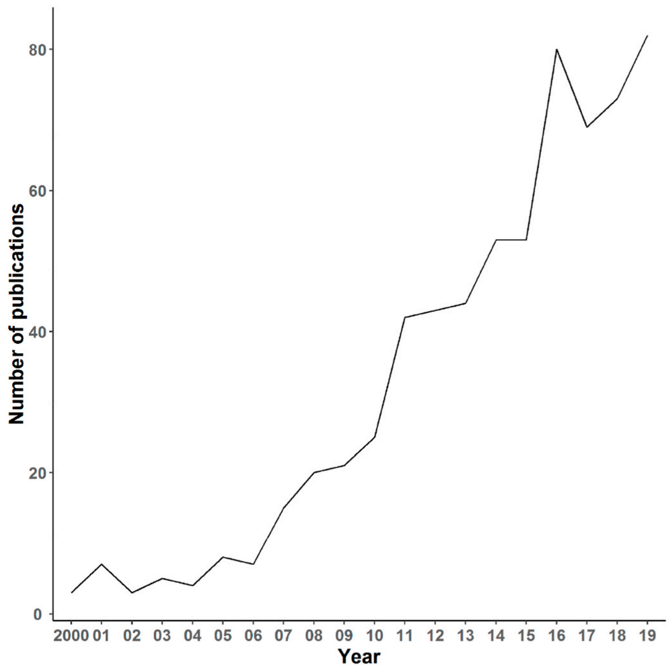

Fig. 5. Distribution of publications over time.

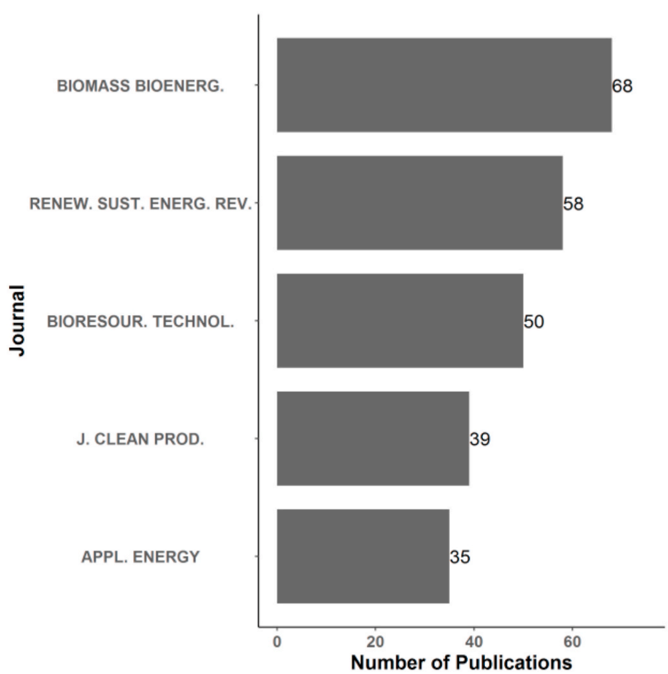

Fig. 6. Distribution of publications by journal.

be beneficial for regular monitor information update. Ahamed et al. (2011) [64] reviewed the most common-use vegetative indices and satellite imagery sensors that can be used for biomass feedstock production system. But the accuracy of land cover classification should also be concerned. Hiloidhari et al. (2017) [47] emphasized that land use classification accuracy should be tested in advance, and the accuracy should exceed 85% is recommended for AR supply planning [47,65]. The quality of the satellite image and land cover classification methods may impact classification performance. Ma et al. (2017) [66] reviewed 173 publications studied land cover classification worldwide with meta-analysis, and they found out that overall mean accuracy of only four types (among twelve) of sensors (UAV, SPOT-5, QuickBird, IKONOS) can exceed 85% (see Fig. 8). Also, they [66] evaluated the accuracy of different supervised classification methods, and concluded that random forest algorithm is better than support vector machines and other methods. Table 1 summarizes the applications of remote sensing technology in bioenergy planning. These examples provide good references for integrating remote sensing technology with AR supply chain design. With the detailed information of AR distribution, better solutions for determining the locations of facility with optimization methods, including mixed integer liner programming [67,68], k-means clustering [69,70], kernel density method [71], p-median model [72], can further

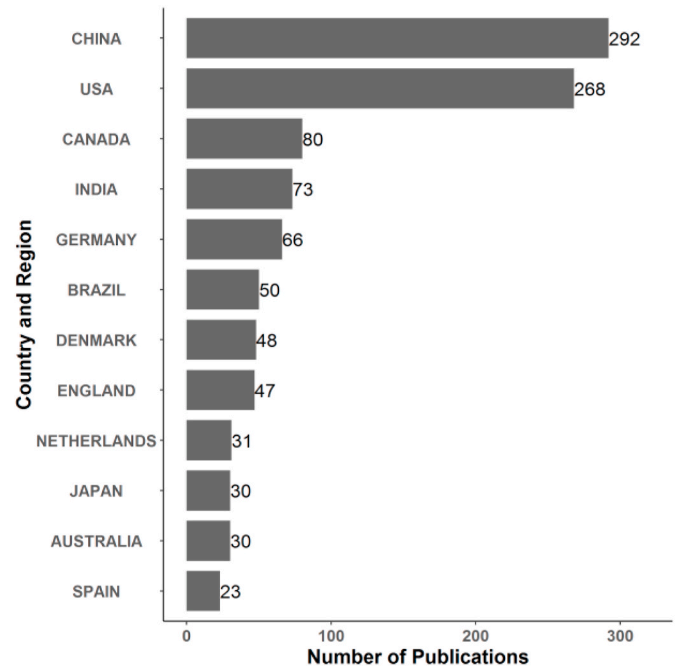

Fig. 7. Spatial distribution of productive countries based on authors' address.

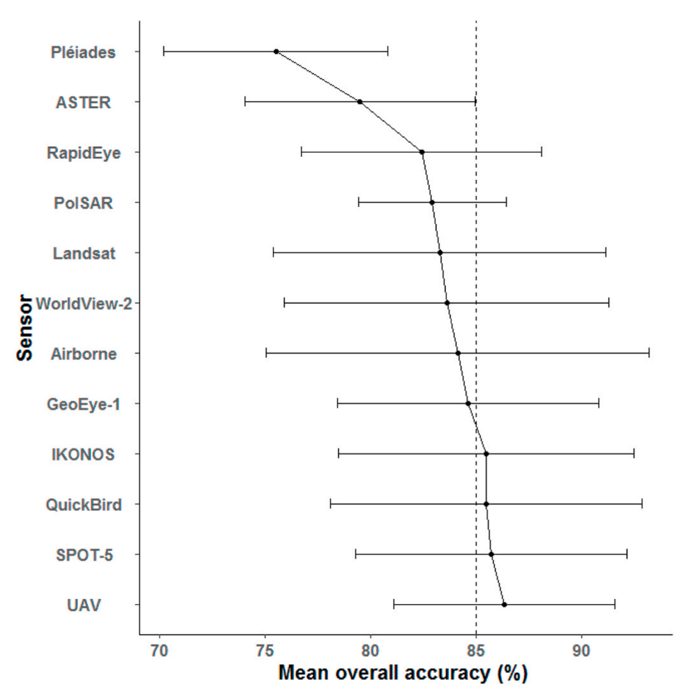

Fig. 8. Mean overall accuracy for different sensor types with standard deviation. The source of data came from Ma et al. (2017) [66].

Table 1
Some examples of remote sensing technology applications in bioenergy planning.

Reference	Remarks	Sensor
[45]	GIS enable analysis of wheat straw logistics system and optimal site selection in Jiangsu, China	MODIS
[56]	Spatio-temporal analysis of the potential role of bioenergy in Mali's energy system	MODIS
[57]	GIS based assessment of rice straw for decentralized electricity generation in India	IRS-P6 (Indian Remote Sensing Satellite)
[73]	GIS based assessment of groundnut and beans residue for comprehensive utilization in Nigeria	Landsat
[74]	The relationship between land use change (with automated satellite image) and biofuel production in USA	National Land Cover Database (data source from Landsat)
[75]	The evaluation of AR for bioenergy utilization in the Indo-Gangetic Plains	MODIS
[76]	GIS enable analysis of rice straw as biofuel for tea drying in Assam, India	IRS-P6 (Indian Remote Sensing Satellite)
[77]	GIS based planning of residue-to-biomethanation power plant in India	IRS-P6 (Indian Remote Sensing Satellite)
[78]	GIS application of rice straw supply for combustion power plan in India	WorldView-2
[79]	Spatial analysis of cereal straw for bioenergy utilization in China	MODIS
[55,80]	GIS based site selection for AR and other biomass power plans in Guangdong, China	MODIS
[81]	Spatiotemporal evaluation of AR for bioenergy utilization in China	MODIS

promote the estimation accuracy of AR transportation.

4. Measures of transportation distance

When AR resource is located and allocated geographically, and positions of bioenergy factories are determined, the transportation distance can be calculated with a series of measurements. Different measurements of AR transportation distance may lead to exaggerate or underestimate the cost of transportation severely. If there are no existing or planned facilities, a hypothetical position can be contrived by user-define [82], or it can be assumed by conventional fuel factories replaced by bioenergy factories [83]. With the geographic coordinates of locations, instant thinking of calculating transportation distance uses straight-line distance (Euclidean distance [58]). Singh et al. (2010) [84] used straight-line distance to estimate the transportation cost of delivering AR to power plant in India. Yu et al. (2012) [35] assumed that the delivery route was straight-line without considering potential geographic obstruction. Cao et al. (2016) [33] demonstrated that they calculated AR transportation between village (the smallest unit of AR resource allocated) and AR transfer stations (warehouses) with straight-line distance. Similarly, Wang et al. (2015) [45] assumed that distance between cropland (paddy field in Jiangsu, China) and transfer stations was a straight line or near a straight line. Huo et al. (2016) [39] also used straight-line distance to estimate maize stover transportation distance. Apparently, many researchers have recognized that straight-line distance seriously underestimates realistic transportation, and an adjustment is introducing tortuosity factor (road-bending factor), which can be regarded as reflecting circuitous and intricate road conditions [58].

The general rule of the tortuosity factor is in croplands with poorer infrastructure (mostly in developing countries), the value should also be raised [85,86]. On the contrary, in developed cropping areas with better transportation conditions or flat terrain, the tortuosity factor could be lower [86]. However, in practice, analysis of traffic infrastructure and road conditions for getting appropriate tortuosity factor is rare. Table 2 gives examples of using the tortuosity factor for estimating the transportation distance of delivering AR or other biomass for bioenergy utilization. Some researchers used the tortuosity factor proposed by others, but failed to explain applicability. Based on personal experience, some researchers assumed the tortuosity factor directly without giving reasons. Hence, Sultana and Kumar (2014) [85] built up a systematic framework for estimating tortuosity factor in biomass transportation with GIS, and such methodology would be beneficial for getting a more accurate tortuosity factor based on local conditions. A case study in western Canada showed that the tortuosity factor could vary between 1 and 3.16.

Table 2
The typical applications of tortuosity factor in AR transportation.

Reference	Factor	Country	Source of value
[15]	$\sqrt{2}$	China	[91]
[20]	$\sqrt{2}$	Greece	[94]
[86]	1.5	Vietnam	personal experience
[87]	1.5	Canada	[88]
[88]	1.5	USA	personal experience
[89]	1.5	China	personal experience
[90]	1.27	Canada	[91–93]
[95]	1.3	India	personal experience
[96]	1.5	China	personal experience
[97]	between 1 and 3	USA	[91]
[98]	1.3 for truck; 1.79 for railroad	USA	[99]
[100]	1.3 for truck; 1.79 for railroad	USA	[99]
[101]	1.5	USA	[102]
[103]	2.14	Sweden	personal experience
[102]	1.5	USA	personal experience
[104]	1.27	USA	[105]
[106]	1.5	UK	personal experience
[107]	1.27	Canada	[91]

Winding factor is another form of tortuosity factor, but many researchers treated it independently. During AR transportation stage, winding factor has a strong influence on AR transportation. So, winding factor is one of explanations that realistic transportation distance is significantly greater than straight-line distance [13]. Bennett and Anex (2009) [108] chose the value of winding factor as 1.2. Instead of designating a specific of winding factor, Leboreiro and Hilaly (2011) [13] conducted a sensitivity analysis to evaluate the influence of different values of winding factor on transportation cost of supplying corn stover for ethanol production in USA. Apart from wind, National Standard “Fuel consumption for trucks in operation” [109] released by Chinese authority summarized a series of tortuosity factors, which are consist of road conditions, temperature, altitudes etc. The parameters of these factors are shown in Table 3. From the given tortuosity factors, a straight line only exists when driving in a first-class highway; temperature is greater than 5 °C but lower or equal to 28 °C; and latitude is lower than 500 m. The highest coefficient of tortuosity factor inferred from Table 3 can reach to 2.3 (1.7 × 1.13 × 1.2). Determination of choosing a specific value of tortuosity factor should be based on local transportation conditions.

Table 3
Tortuosity factor from National Standard “Fuel consumption for trucks in operation” in China [109].

K	First	Second	Third	Fourth	Fifth	Sixth
	1	1.1	1.25	1.35	1.45	1.7
t	$t \le -25$	$-25 < t \le -15$	$-15 < t \le -5$	$-5 < t \le 5$	$5 < t \le 28$	$t > 28$
	1.13	1.09	1.06	1.03	1	1.02
H	$H \le 500$	$500 < H \le 1500$	$1500 < H \le 2500$	$2500 < H \le 3500$	$H > 3500$	
	1	1.03	1.07	1.13	1.2	

Note: K, t and H represent class of road conditions, monthly average temperature (°C), and altitude (meter) respectively.

Whether using straight-line distance directly or adjustment with tortuosity factor, travelling routes of AR transportation are unknown. Another more popular way is using traffic road networks in AR supply chain. To overlap different types of map (administrative, AR distribution, road network etc.) into a final map, bioenergy factory locations can be optimized in accordance with the shortest transportation distance (lowest cost-efficient) constraints [110]. Calderon et al. (2017) [111] proposed a complicated framework to evaluate the economics of supply AR and other biomass for producing synthetic natural gas in the UK. In their study [111], mixed integer linear programming (MILP) model was implemented on UK road network to optimize the transportation distance and cost. Similarly, Zimmer et al. (2017) [112] evaluated the delivery cost of AR and other biomass to produce biofuel for transportation sector by implementing MILP model on the Chilean traffic network. Another way to find the shortest transportation is via pathfinding. In ArcGIS, follow the instructions of Network Analyst extension can assist the users to model the cost-efficient travelling routes for designing an AR supply chain [47]. As for the first published pathfinding algorithm [113,114], Dijkstra is popular in computing optimal travelling route between specified start and goal nodes (cropland and bioenergy factories), thereby optimizing the geographic selection of facility location in the sustainable AR supply chain [19,115,116]. In the future, algorithm comparison (Astar, genetic, Floyd, etc. [117]) and algorithm improvement [118] can be implemented for further travelling routes and transportation distance optimization.

There is a trend that using emerging electronic navigator applications, which can also help to illuminate and enlighten improvement of AR supply chain. With the development of state-of-the-art navigation applications, using paper maps is decreasing dramatically. The survey for drivers towards the use of navigators in 2019 [119] illustrated that only 4.4% of respondents still insisted on paper maps. Apart from another 9.8% of respondents who were driving without any navigator, the rest of respondents chose at least one type of electronic navigators. A survey on over 500 smartphone owners about their reliability on electronic navigator applications [120] showed that more than 77% of smartphone owners use navigation applications routinely, and Google Maps is the most popular application (more than 67% of respondents). Because the services of Google are unavailable in China, other domestic applications are filling the gap. According to survey data in China [121,122], users of smartphone's navigator applications were over 0.72 billion people in 2018 (accounted for 51.43% of the total population), and the most popular applications were AMAP (60.1%) and Baidu Maps (58.8%). In academia, a new adjustment in publications is proposed to accommodate electronic navigation applications for AR transportation. Elsevier journals including Bioresource Technology launched with an alternative three-pane article view form, and the middle pane features could be enriched with Google Maps [122], to achieve better visualization performance for facility locations and AR transportation routes optimization.

Note: The degree of using these applications can be categorized as follows: (1) "*" only report a statement that they used Google Maps or Baidu Maps (without citation); (2) "**" citations were given; (3) "***" visualization of facility locations and transportation routes was provided.

There are plenty of advantages of using these electronic navigator applications in AR supply chain. To begin with, the geographical information, such as the newly constructed traffic infrastructure or the availability of specific traffic route, can be updated regularly. Also, the consistency of theoretical and realistic AR transportation route design can be guaranteed. Users can be beneficial for free electronic navigator applications (access through smartphone or computer), instead of owning professional navigator. Therefore, using these electronic navigation applications can promote the precision of estimating AR transportation distance and further optimize AR supply chain. The current implementations of Google Maps and Baidu Maps are summarized (19 pieces of article) and discussed how they were performed in AR supply chain optimization (see Table .4). The degree of using these applications can be categorized as follows: (1) "*" only report a statement that used Google Maps or Baidu Maps (without citation); (2) "**" citations were given; (3) "***" visualization of facility locations and transportation routes was provided. The result shows that the implementations of these applications are in the early stage, and most of the researches (79%) were only treated them as online distance calculators. In fact, more functions in these applications can be remarkably beneficial for optimizing transportation distance, thereby reducing the supply cost of AR for bioenergy utilization. They have functions of not only providing geographically shortest pathway with clear navigation instructions and time reminder, but also providing the cheapest pathway (avoiding the use of expressway) or the most time-saving pathway (longer journey but fewer traffic flow and traffic lights, according to analysis on historical traffic congestion data). These functions can satisfy diverse demands of AR transportation to some extent.

Learning difficulty is one of the major obstacles of manipulating these applications, especially for non-professional users. Hence, in order to fill in the gaps, a comprehensive method for manipulating Baidu Maps for distance estimation, travelling route optimization and graphical visualization is proposed, and it is compiled via R software, which could be easy to reproduce the works according to user-defined requirements. An example of AR transportation in Nongan county, China, is shown in Fig. 9. In Baidu Maps application, three types of tactics can be used for transportation route design: shortest distance, shortest time and no expressway (optional). In tactic 1, the transportation route with shortest distance is given. The transportation distance is 176 km, but the truck needs to pass 12 traffic lights, and predicted time consumed is 4 h and 30 min. In tactic 2, the transportation route with shortest time is designed. Although the transportation distance would raise to 263 km, the predicted time consumed is 3 h and 57 min. With the use of expressway, it would spend over 260 CNY for payment. Tactic 3 is the optional route when tactic 1 and tactic 2 are unavailable. The transportation time is 4 h and 20 min, and the distance is 186 km. This route avoids using the expressway, and truck needs to pass 24 traffic lights. For more technical details and source codes, a step-to-step tutorial is written for reference (see supplement). This method can be used independently or embedded as a submodule in the AR supply chain.

5. The variability of vehicle arrangements

AR has the features of low value and low density [142], and the cost

Table 4
The degree of using Google Maps and Baidu Maps in AR transportation.

Reference	Country	Product	Degree of use
[123]	Germany	Bioethanol	*
[124]	USA	Bioethanol	***
[125]	China	Biofuel	**
[126]	Malaysia	Electricity	***
[127]	Germany	Bioethanol	*
[128]	UK	Bioethanol	**
[129]	Australia	Electricity	*
[130]	Brazil	Bioethanol	**
[131]	Philippines	Electricity	*
[132]	China	Electricity	*
[133]	USA	Electricity	*
[134]	Brazil and Sweden	Marine biofuel	**
[135]	Ghana	Bioethanol	*
[136]	Germany	Biodiesel	**
[137]	USA	Bioenergy with Carbon Capture and Storage	**
[138]	Spain	Bioethanol	*
[139]	Slovenia	Biogas and electricity	***
[140]	Slovenia	Biogas	***
[141]	Thailand	Fuel briquette	*

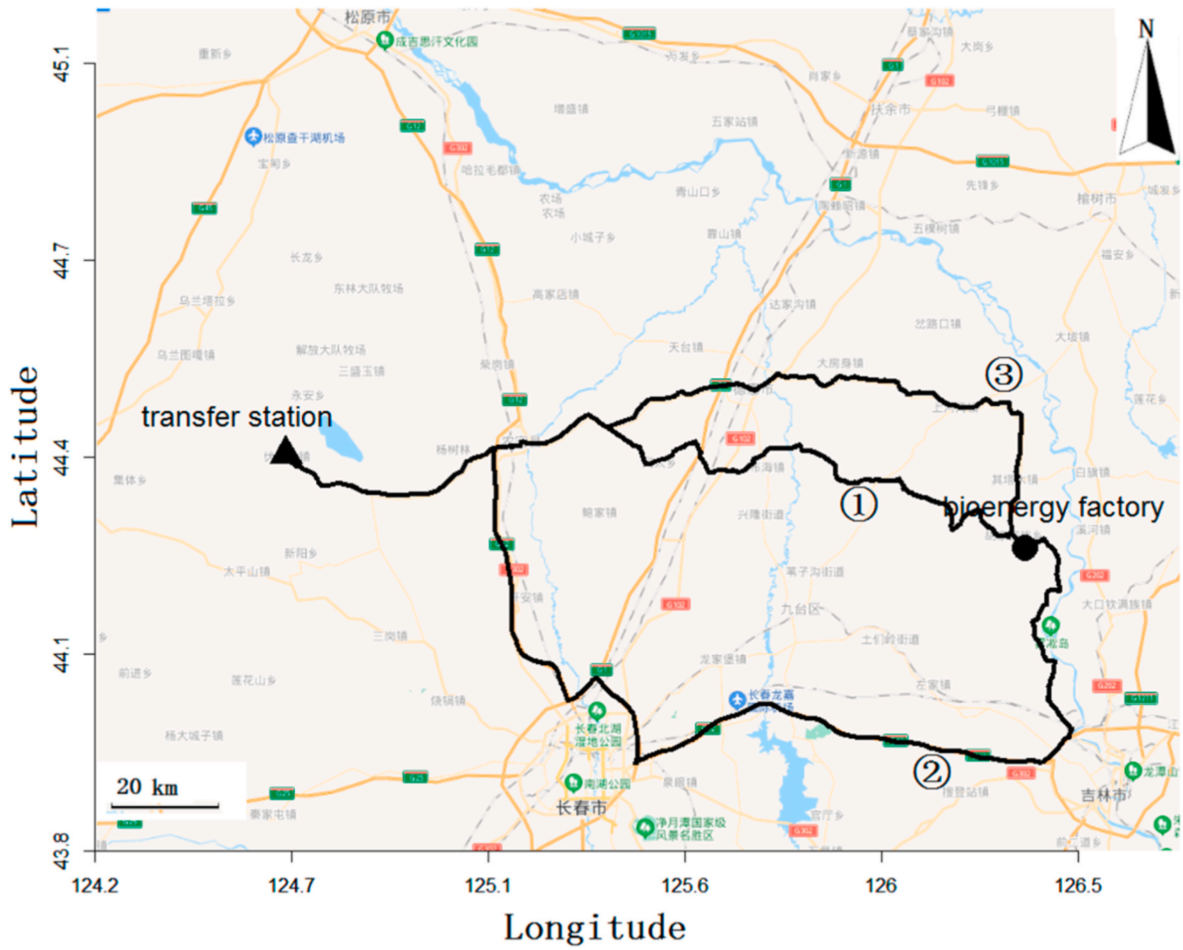

Fig. 9. Simulation of travelling routes for transporting AR from transfer station to bioenergy factory with Baidu Maps in Nongan county, China. , ② and ③ represent three tactics (shortest distance, shortest time and optional no expressway) of travelling routes.

of AR transportation is remarkably greater than conventional fossil fuel [143]. So, choosing the appropriate transport modes can be beneficial for reducing AR transportation costs. In general, trains and ships are suitable for long distance transportation. Taking advantage of coast location in the Gulf of Mexico, transporting corn stover in Florida by ship is one-tenth or a half of variable cost than trucks, or trains [144]. However, the procurement cost of different vehicles has significant disparity, and fixed costs of trains or ships are remarkably higher than trucks in AR transportation [144]. Mahmudi and Flynn (2006) [145] compared the AR transportation cost of trains and trucks in Canada, and they concluded that using trucks could be cheaper when the distance was below 170 km. Searcy et al. (2007) [146] estimated that, using trucks or ships in USA was economical when AR transportation distance should exceed 500 km or 1500 km respectively. Considering the availability of rails and sea/river [146] and distance of AR transportation, road transportation is the mainstream for AR transportation [142].

Apart from evaluating the cost and profit in AR supply chain, environmental performance is also raising more and more concerns, and reducing greenhouse gas emissions in AR supply is another goal in optimization [19,147]. In AR transportation activity, the mainstream of measuring greenhouse gas emissions is through the emissions of fuel consumption by the vehicle. There is no doubt that, for different types of vehicle, their emissions during transportation were significantly different [148,149]. Nevertheless, the variability of same type of vehicle cannot be underestimated. Taking truck transportation as an example, one of the popular ways to calculate the emissions for truck transportation in the USA is via US.EPA's Smartway program [150,151], which presents information on emission factors for dominant brands of trucks. Researches of AR supply chain with life cycle assessment always reported the parameters of truck fuel consumption for transportation. Here, a summary and comparison of CO_2 emission factor of truck transportation between USA (parameters from Smartway flatbed) and China (parameters from LCA case studies) are shown in Table 5. Table 5 reveals that variability existed in truck transportation, and the range of CO_2 emission factor were 17.4 and 133.37 g/ton/km in USA and China, respectively. It means that, the different selection of truck would bring the different gap of environmental impact in AR transportation.

Note: The parameters reported in China were diesel consumption for truck transportation (unit was L/ton/km), and they were unified by common conversion factor of diesel to CO_2 released by IPCC (10180 g of CO_2/gallon of diesel [67,166,167]).

The gap provides an idea of optimization in AR transportation with a cleaner choice of vehicle selection. If the average trucks of AR transportation in USA and China can apply to the trucks with minimum emission, a significant emission reduction potential could be achieved in AR transportation (19% and 66% in USA and China respectively). The present problem for optimization is the information of trucks used in AR transportation is insufficient. Devlin et al. (2013) [168] and Cheng et al. (2020) [153] mentioned that the trucks used for transportation were

Table 5
The CO_2 emission factor of truck transportation (g/ton/km) in USA and China.

Country	Minimum	Mean	Maximum	Range	Source
USA	39.46	48.51	56.86	17.4	Smartway [150,152]
China	39.8	117.01	173.17	133.37	[28,38,39,153–165]

2004 DAF XF and Jiefang J6M-8 × 4, and this information provides a reference for designing future AR transportation. But most of the researches did not report brand name and reason for using a specific truck for AR transportation. Therefore, the selection of trucks should be cautious and persuasive. The means of cleaner energy production should also be cleaned simultaneously. In order to avoid selection bias, it is suggested to construct a vehicle database in AR transportation, which is including brand name, purchase price, weight, carrying capacity, fuel consumption, availability and so on. With such a database, it can provide a more suitable choice to reach the local needs, and can satisfy objective goals in AR transportation optimization, such as capital investment saving, operation cost saving or environmentally friendly.

6. Patterns of (de)centralized transportation

Patterns of AR transportation can be split into centralized and decentralized transportation [169,170]. Centralized transportation is carrying AR from cropland to bioenergy facilities directly, whereas decentralized transportation is using transfer stations (warehouses) between cropland and bioenergy factories [33,170]. The transportation distance has the direct effect of deciding the (de)centralized patterns. Considering the cost and profit of different types of bio-product, the AR transportation radius is thereby can be optimized by economical constraints. Based on the cost-profit analysis, Ma et al. (2015) [42] reported that optimal AR transportation radius for AR gasification, bioethanol, combined heat and power cogeneration and briquetting fuel production were 37, 35, 22 and 4 km respectively in Heilongjiang, China. A field survey from Zhai et al. (2016) [171] reported that the average transportation distance from cropland to AR power plant was 3 km in Jiangsu, China. Because the construction and operation of AR transfer stations would bring extra cost [20], for the bioenergy project that can be satisfied with the short-distance supply, to transport AR directly could be cheaper.

On the other hand, for the larger-scale bioenergy production, the requirement of AR feedstock is usually greater. The longer collectable radius would cost more time in AR transportation. The fresh residue after harvesting contains high moisture (e.g., 50–70% in corn stover [172], 60–70% in rice straw [173]), and it is perishable [174] because fermentation would be commenced when moisture is over 25% [25]. Due to the restricted time of AR removal and uncertainty of weather change (rain or snow), natural drying sometimes is difficult. And if AR is exposed in the field and its collection and storage are being delayed, due to the occurrence of fungal deterioration, dry matter losses would be much severely [175]. For decentralized transportation, collecting and transporting AR from cropland to nearby transfer stations could save time, and using pretreatment equipment (densification or torrefaction) in every transfer station could achieve the goals of cost-saving or quality maintenance. Mupondwa et al. (2012) [176] conducted a techno-economic analysis of comparing direct bale AR and pellet transportation, and they reported that transporting pellet could be cheaper when the distance was over 250 km. Chiueh et al. (2012) [177] reported that, coordinate with torrefaction, decentralized rice straw transportation can achieve more significant cost reduction than centralized transportation. In addition, besides the economical and quality consideration, local worry of AR conflagration is encouraged to choose decentralized transportation. AR with high moisture content induces fungi growth due to digestion of nutrients that could reduce heating value as well as generate spontaneous heating causing self-ignition [178,179]. So, in view of high flammability [180], “not-in-my-back-yard” attitude from the public is one of the tough opposition that may occur the failure of bioenergy projects’ construction and operation [181,182]. Equipped with fire control measures and flexible location selections, transfer stations can scatter more conflagration risks by storing AR in pellet or briquette form.

The selection of vehicles could be more flexible in (de)centralized transportation. Due to bad road conditions in rural areas, feasible types of vehicles are restricted. Considering the realistic conditions of rural roads in Taiwan, China, Chiu et al. (2016) [60] pointed out that the weight of trucks used for carrying rice straw from paddy fields to transfer stations cannot exceed 3.5 tons. Deployment of transfer stations is closed to highway or railway stations intentionally, so for transportation between transfer stations and bioenergy factories, using heavy-duty trucks or trains could significantly reduce unit transportation costs. Under the same bioenergy production scale, Liu and Bao (2019) [170] concluded that the decentralized AR transportation cost is remarkably lower than that of the centralized AR transportation. Yu and Fan (2009) [41] estimated that unit transportation cost in transporting AR from cropland to transfer stations and from transfer stations to bioenergy factories were 1.5 and 1 RMB/ton/km respectively, whereas the estimation from Yu 2011 [183] were 1.2 and 0.6 RMB/ton/km respectively.

The brokers’ participation in AR transportation is another concerning factor that influences the decision of (de)centralized transportation patterns. In developing countries, croplands are in small pieces owned by millions of household farmers [14,33]. Data from FAO [11] illustrate that, in 2017, arable land per farmer (rural population) in China, India and Thailand were 0.20, 0.18 and 0.48 ha respectively, whereas in Australia, Belgium and USA were 8.92, 3.59 and 2.71 ha respectively. With the increase of mechanization in developing countries, some researchers assumed that farmer-owned tractors could be used in AR transportation [14,30,39]. But the disagreement was proposed from other researches [20,24]. To begin with, farmers are busy harvesting or planting for next-season crops, both agricultural machines and labour are intensive [24]. Because of the relatively low economical simulation of selling AR, farmers would not endure any inconvenience or impediment with harvesting [25]. Emissions from tractors are significantly greater than trucks in transportation [184], and the low carry capacity of tractors increases the idle transportation frequencies [185]. On the other hand, due to the harm of long-term excessive residue return to cropland or strict prohibition of residue open burning, sometimes farmers are willing to transport AR voluntarily. But Wang et al. (2015) [45] investigated that the maximum distance farmers could tolerate by themselves was 5 km. Such distance cannot satisfy the needs of large-scale bioenergy projects. There is a dilemma that the time of AR collection and transportation are short, and to keep the AR in good quality. Therefore, the “bridge” between farmers and bioenergy factories, brokers, are emerged. In some regions, bioenergy factories outsource the work of AR collection and transportation works, and they purchase AR from brokers directly [174,186–189]. Brokers are farmers who have a commercial mind and good communication capacity [190]. They have a good personal relationship with local farmers, and they can collect and transport the AR from farmers more easily. According to the cost-profit assessment of AR supply, brokers can choose (de)centralized transportation patterns and vehicle arrangements [164]. For bioenergy factories, they can spread the risk of AR supply (the costs of vehicle procurement and driver recruitment are huge [191]), and concentrate their attention on bioenergy production. In addition, instead of negotiating with myriads of farmers for AR supply [164], bioenergy factories can propose the procurement requirement with brokers to control the quality of AR. For example, to require moisture of AR does not exceed a specific standard (17%, e.g.). Good incorporation with brokers can make sure that AR supply could be sustainable, thereby influencing the successful operation of bioenergy projects.

7. Conclusions and future perspective

In this critical review, various researches that were implemented to optimize AR transportation had been synthesized. To begin with, a comprehensive bibliometric analysis of papers using the Web of Science from 2000 to 2019 was performed. The number of publications on AR supply chain has risen. Most articles on AR supply chain were published in Biomass and Bioenergy, and Chinese research institutes have the most enthusiasm for studying AR supply chain. Considering that AR transportation occupies one-fourth of total supply cost, optimizing AR transportation activity can remarkably reduce the feedstock cost for bioenergy production. Based on the progressive relationship of factors, the optimization of AR transportation was divided into the distribution of AR resource in cropland, measurements of estimating transportation distance, vehicle selection of AR transportation, and (de)centralized transportation patterns.

One of the main findings is that, due to the spatial distribution of AR in cropland, the land cover classification method with remote sensing technology would be helpful for determination of bioenergy facility locations. After comparing a diversity of measurements to AR transportation, electronic navigator applications (Google Maps or Baidu Maps) have been suggested, because they could provide up-to-date information, realistic travelling routes and are free for users. In order to overcome the difficulty of manipulating Badiu Maps, a step-by-step user tutorial was compiled for whomever would like to implement this application in AR transportation optimization. The variability of vehicle arrangements is discussed and a vehicle database for AR transportation should be established to provide a more suitable choice to satisfy the local needs and avoid selection bias. The decision of choosing (de) centralized transportation patterns can be affected by the AR transportation distance, the requirement of AR pretreatments, and brokers' participation.

This review is an important contribution to improving knowledge on the optimization of AR transportation. The technical detail discussed is especially useful for researchers and bioenergy project investors who intend to reduce the AR transportation cost in the future, especially for developing counties.

Conflicts of interest

The authors declare no conflict of interest.

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Appendix A. Supplementary data

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