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Multiperiod stochastic programming for biomass supply chain design under spatiotemporal variability of feedstock supply

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ABSTRACT

Spatiotemporal uncertainties in the collection of crop residues pose great challenges to the development of a long-term and economic biomass-to-biofuel supply chain network (BSCN). A multiperiod stochastic programming (SP) model considering uncertain collectible corn stover removal and farmer participation rates is developed. The SP model is compared with the deterministic programming for the expected scenario (DPES) model to provide decision-making support for BSCN in two different periods. With the statistical results of separate deterministic programming models for each scenario generated randomly based on the normal distribution as a reference, the economic performance of the SP and DPES models is compared in the model development period and then confirmed in the model validation period. A county-level case study with a 10-year development and a 3-year validation period is applied. The economic performance of the SP model is comparable to that of the DPES model in the development period, and the SP model achieves much higher cost savings in the validation period. Although biomass transportation cost is the most unstable cost component, the variation in bioethanol production cost is largely consistent with that in biomass purchase cost. The SP model demonstrates stronger robustness to uncertainty than the DPES model.

1. Introduction

With the increasing concern about global warming and increasing requirements to reduce greenhouse gas (GHG) emissions, biofuels are gaining more attention as alternatives to fossil fuels [1–4]. Bioethanol, an important component of biofuels, can not only partly replace gasoline in the transportation sector but also considerably reduce GHG emissions [5–9]. Use of lignocellulosic bioethanol can reduce the potential threat of first-generation bioethanol production to food security accompanied by future population growth on the basis of meeting the polity requirements of biofuel substitution to achieve carbon neutrality [2,3,10,11]. Hence, establishing a stable and reliable biomass-to-biofuel supply chain network (BSCN) is extremely important for achieving cost-effective and eco-friendly bioethanol production and consumption systems.

The BSCN is a complex system that consists of four major subsystems: production, processing, distribution, and utilization [12–14]. A biomass production subsystem is spatially and temporally explicit and sensitive to changes in climate and weather patterns [15–17]. It depends on local environmental factors, such as weather and soil properties, and is affected by farm management capabilities and infrastructure [18,19]. Fluctuations in agricultural productivity pose considerable challenges for the design and operation of integrated biomass supply chain systems that combine productivity with farm management decisions within the context of large-scale supply chains [20,21]. Therefore, a key challenge for biomass supply chain modeling is to incorporate the spatiotemporal uncertainties of agricultural production to support planning and management decisions.

Systematic analysis is critical for understanding the interactions among subsystems and for improving the efficiency and effectiveness of the entire BSCN system. Many BSCN studies have applied deterministic programming (DP) to minimize production costs or maximize profits [22–24]. Considering the variations in biomass supply, consumer demand, procedure parameters, and feedstock and product prices, quantitative sensitivity analyses have been

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Nomenclature

Sets

I	Set of counties supplying biomass, indexed by i
J	Set of counties that may construct a centralized storage and preprocessing (CSP) facility, indexed by j
K	Set of counties that may construct a biorefinery, indexed by k
T	Set of time stages, indexed by t
S	Set of scenarios, indexed by s
L	Capacity level of a facility, indexed by l

Parameters

ρ^s	Probability density in scenario s (−)
$b^{i,t,s}$	County-level biomass availability in year t of scenario s (Mg)
$c^{i,t,s}$	County-level biomass farm-gate price in year t of scenario s ($/Mg)
cf_{cs}	The fixed price of producing biomass ($/Mg)
cv_{cs}	The variable price of producing biomass ($/ha)
$y^{i,t,s}$	County-level biomass collectible yield in year t of scenario s (Mg/ha)
$y_c^{i,t}$	County-level corn yield in year t (Mg/ha)
$b_c^{i,t}$	County-level annual corn production in year t (Mg)
η_{sh}	Corn stover harvest index, meaning the ratio to the total corn biomass (−)
η_{gh}	Corn grain harvest index, meaning the ratio to the total corn biomass (−)
η_c^s	Collectible corn stover removal rate in scenario s (−)
η_p^s	Farmer participation rate in scenario s (−)
t_{v1}	The variable transportation cost of raw biomass ($/Mg/km)
t_{v2}	The variable transportation cost of preprocessed biomass ($/Mg/km)
t_{f1}	The fixed transportation cost of raw biomass ($/Mg)
t_{f2}	The fixed transportation cost of preprocessed biomass ($/Mg)
Q_{bf}^t	Total biomass feedstock used to produce bioethanol in year t (Mg)
$d^{i,j}$	Distance between biomass supply county i and CSP j (km)
$d^{j,k}$	Distance between CSP j and biorefinery k (km)
s_{op}	Unit operating cost for a CSP ($/Mg)
s_v^l	Variable capital cost for a CSP at level l ($/Mg)
s_f^l	Fixed capital cost for a CSP at level l ($)
s_{lowcap}^l	Lower capacity limit of a CSP at level l (Mg)
s_{upcap}^l	Upper capacity limit of a CSP at level l (Mg)
α	Annualized cost factor (−)
β	Biomass loss rate at a CSP (−)
b_{op}	Unit operating cost for a biorefinery ($/Mg)
b_v^l	Variable capital cost for a biorefinery at level l ($/Mg)
b_f^l	Fixed capital cost for a biorefinery at level l ($)
b_{lowcap}^l	Lower capacity limit of a biorefinery at level l (Mg)
b_{upcap}^l	Upper capacity limit of a biorefinery at level l (Mg)

Decision variables

$f^{i,j,t,s}$	Amount of biomass flowing from supply county i to CSP j in year t of scenario s (Mg)
$f^{j,k,t,s}$	Amount of biomass flowing from CSP j to biorefinery k in year t of scenario s (Mg)
$p^{t,j,l}$	The CSP capacity in county j at level l in year t (Mg)
$o_S^{t,j,l}$	Binary variable indicating whether there is a CSP located in county j at level l in year t (−)
$q^{t,k,l}$	The biorefinery capacity in county k at level l in year t (Mg)
$o_B^{t,k,l}$	Binary variable indicating whether there is a biorefinery located in county k at level l in year t (−)

extensively conducted using DP to quantify the effect of input parameters on the object of interest [14,20,25]. However, uncertainty is widespread in agricultural production, especially for long-term optimization, which leads to challenges and risks for stable operation and sustainable profits of related industries [26–30]. Therefore, establishing a BSCN with high spatial and temporal stability dealing with the uncertainties in agricultural production is imperative for return on investment and industrial development.

Stochastic programming (SP) has been widely used to quantify the effect of uncertainties on the optimal design and operation of BSCNs [31–34]. The challenges in a supply–refinery–consumer BSCN were analyzed by constructing a stochastic mixed-integer linear program (SMILP) and sensitivity analyses were performed for different uncertainties [31]. Profit under uncertain feedstock types, prices, supply and demand is gaining increasing attention. In general, SP under uncertain parameters exhibits a higher economic profit than DP [35–37]. In previous studies, the study regions range from individual provinces to entire countries, and the study periods range from individual seasons to years [38–41]. Table 1 summarizes recent studies on the BSCN considering parameter uncertainty. Although the spatial variation of strategic and tactical decision variables of SP-based BSCN under a single period has been studied, the spatiotemporal variation of BSCN consisting of strategic and tactical planning decisions such as facility location and flow pattern has not been explicitly studied considering the annual changes of uncertain parameters under long-term planning, and the economic superiority of the developed SP-based BSCN has rarely been validated in other periods.

The major contributions of this study can be summarized as follows: (1) a multiperiod SP model for BSCN considering the long-term uncertainty of supply due to natural and social factors is developed; (2) procurement price uncertainties are determined by the constructed relationship between purchase price and biomass supply rather than by artificially fluctuating percentages, thus avoiding the extreme scenario of high production accompanied with high price; (3) intervals of uncertain parameters and their probability distributions are set up based on historical surveys, implying a good representation of reality; (4) the statistical spatiotemporal variation of strategic and tactical variables for long-term and large scenarios of SP and deterministic programming for the expected scenario (DPES) models are explicitly displayed and compared to that of a DP model for each scenario; (5) the economic superiority of SP model is compared to that of the DPES model in the model development period and then confirmed in the model validation period, clearly demonstrating the advantage of the SP model in dealing with long-term uncertainty; (6) the variation rule of each cost component with uncertain scenarios and investment periods are deeply analyzed and the sensitivity components are revealed.

Combining the historical patterns of biomass yield with spatial-specific information is critical for quantifying the spatial and temporal changes in a biomass supply configuration. In general, one of

Table 1
Review of BSCN studies on spatial and temporal variation of decision variables.

Article	Model	Uncertainty	Results			
			Period	Strategic variables	Tactical variables	Economy
[42]	SP	Supply	1 year	Facility location	Commodity flow	Total cost breakdown
[20]	SP	Supply; demand	1 year	Facility location and capacity differences between SP and DP	/	Total cost comparison between SP and DP
[41]	SP	Supply; demand; price	4 seasons	Facility location and capacity; Conversion technology;	Biomass and biofuel inventory	Expected total profit comparison between SP and DP
[17]	SP	Demand	1 year	Facility location and capacity	Routing distance	Total cost; CO_2 emission
[38]	RP	Supply; demand; economy; environment; society	1 year	Facility location and capacity;	/	Total cost; total environmental impacts; total social impacts
[33]	SP	Supply	1 year	Facility location and capacity; Land allocation	Biomass surplus and shortage	Total cost breakdown
[43]	SP	Demand	3 months	Facility location and capacity	Commodity flow	Total cost breakdown
[29]	SP	Supply; disruption	4 seasons	Facility location and capacity	Commodity flow	Total cost breakdown; total cost comparison between SP and DP
[44]	RP	Demand; price; environment	1 year	Facility location and capacity; conversion technology; land allocation	Commodity flow; inventory level	/
[45]	SP	Demand	5 years	Spatiotemporal variation of facility location	Commodity flow; transportation mode	Total cost breakdown
[35]	SP	Supply; price	10 years	Land allocation	Commodity flow	Total profit comparison between SP and DP
[40]	SP	Supply; demand; price	10 years	Spatiotemporal variation of facility location and capacity; land allocation	Commodity flow	Sensitivities of uncertain parameters on total profit
This study	SP	Supply due to natural and social factors	10-year development period and 3-year validation period	Spatiotemporal variation of facility location and capacity between SP and DPES;	Spatiotemporal variation of commodity flow and its difference between SP and DPES	Total cost breakdown; scenario-based and year-based variation of each cost component; economic evaluation and comparison between SP and DPES

SP: stochastic programming. DP: deterministic programming. DPES: deterministic programming for the expected scenario. RP: robust programming.

the major uncertainties in BSCN design is the spatiotemporal distribution of biomass feedstock supply owing to changes in natural and social characteristics [35,46,47]. Annual biomass yields vary for agricultural residuals and perennial energy crops because of weather variations or climate change [15,48]. Temporal uncertainty changes in biomass yield considerably affect the optimal supply chain configuration, particularly for long-term planning.

In existing studies, biomass feedstock and purchase cost fluctuations are directly input as uncertain parameters [32,40]. However, we analyze the sources and derivations of these fluctuations from natural and social factors. The fluctuations in internal factors that influence the available feedstock supply and purchase cost are considered as uncertain parameters. The amount of crop residue that farmers are willing to collect and provide remains unknown. Feedstock prices, environmental concerns, capital investment, limited operating windows, and additional farm managerial knowledge are all major factors that affect the willingness of the farmers to supply biomass [49–51]. Several surveys have been conducted to understand the behavior of farmers. In Iowa, United States, 17% of the surveyed farmers expressed interest in harvesting corn stover while 37% were undecided [51]. In Missouri and Illinois, under ideal conditions, farmers supply 40% and 32% of their corn stover to biomass processors, respectively [50]. However, excessive stover removal from fields increased the concerns of farmers regarding environmental damage in the field and reduced their motivation to provide corn stover to the biofuel industry [51].

This study aims to develop a multiperiod SP model to provide decision-making support for BSCN by considering the uncertainties in long-term biomass-to-bioethanol refining. A case study is conducted to explicitly quantify the differences between SP and DPES models in two different periods, that is, the model development and model validation periods, and to quantify the effect of biomass supply uncertainty resulting from natural and social conditions on the optimal spatiotemporal distribution of BSCN. The remainder of this paper is organized as follows. Section 2 will introduce the fundamental problem statement, including the detailed structural components, main assumptions, and sources of uncertainties. Section 3 will describe the detailed mathematical formulation of the developed SP and DPES models, including the object function and constraints. A case study of converting corn stover to bioethanol in Illinois will be conducted in Section 4 and the numerical results will be provided and discussed in Section 5. At last, Section 6 will summarize the main conclusions and provides suggestions for future researches.

2. Problem statement

This study aims to analyze the effect of uncertainty in biomass feedstock availability resulting from natural and social factors in long-term planning on the spatiotemporal distribution and economic costs of BSCN. Annual fluctuations in biomass feedstock production, farmer participation rate to provide crop straw, and collectible biomass removal rate from the field are the main factors that affect the supply of biomass and the configuration and costs of BSCN. A multiperiod SP model is developed to optimize the design and planning of the BSCN under uncertain conditions and to

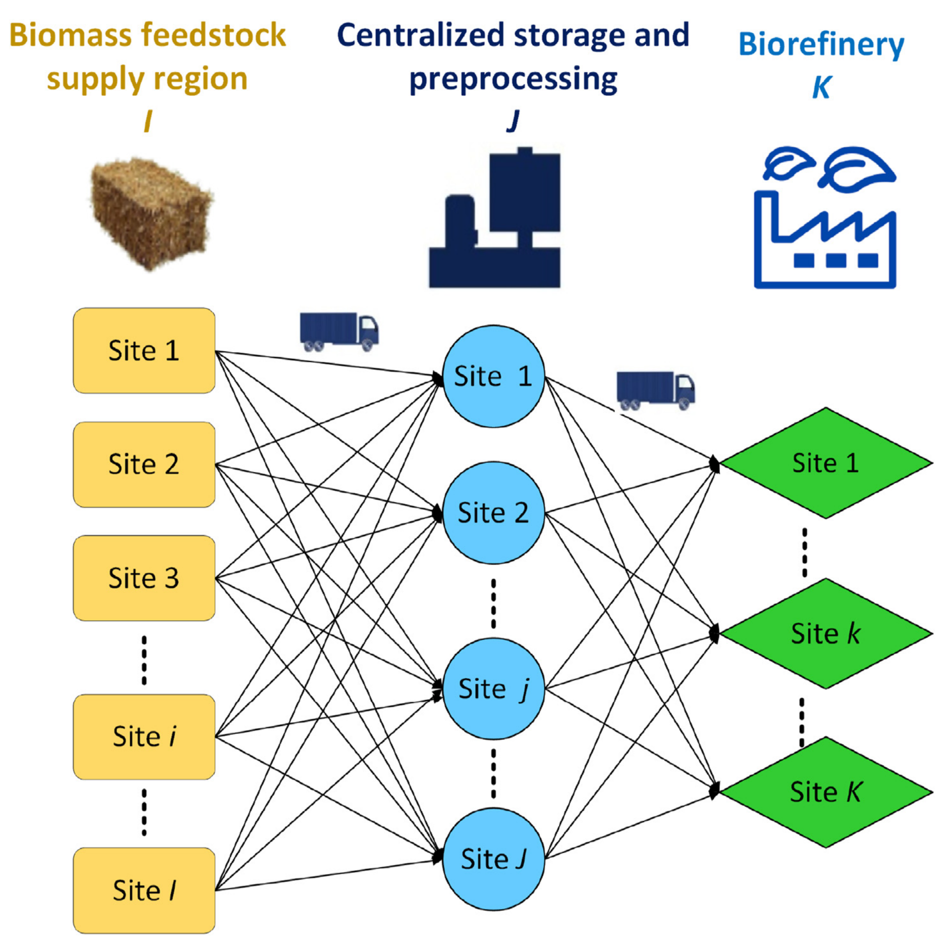

Fig. 1. Three-echelon BSCN superstructure.

minimize the overall expected cost of an integrated BSCN over the entire planning period considering different biomass supply scenarios.

The BSCN superstructure that we intend to establish is illustrated in Fig. 1. The BSCN is comprised of three consecutive echelons, that is, biomass feedstock supply region, biomass centralized storage and preprocessing (CSP), and biomass-to-biofuel biorefinery. The biomass purchased from biomass feedstock supply region i is transported by truck to CSP j for chopping, milling and densification. The preprocessed biomass is then transferred by truck to biorefinery k to refine biofuels. The distributed CSP and refinery configuration is applied in this study, that is, the biorefinery could not store raw or preprocessed biomass, so the biomass feedstock could not be directly transported to the biorefinery.

The following assumptions are made in this study: (1) the biomasses are preprocessed in the same center where they are stored; (2) strategic facilities such as CSP and biorefinery are identified at the beginning of the long-term planning and remain unchanged for the rest of the period; (3) the biofuel demand or the refining capacity of the biorefinery remains constant during the planning period; (4) the grass-to-grain ratio is constant; (5) road haulage by truck is the only mode of transportation.

In the multiperiod SP model, decisions related to long-term supply chain configurations, such as CSP facilities and biorefinery plants, are considered as the first-stage decisions or strategic variables that cannot be changed throughout the planning period, whereas short-term decisions such as transportation flow, which change annually to adapt to variations in biomass supply, are considered as the second-stage decisions or tactical variables [45]. The decision variables include 1) optimal numbers, locations, and capacities of strategic facilities, 2) optimal purchase volume of biomass from each supplier, and 3) optimal biomass transportation flow. For convenience, all the parameters and decision variables are summarized in the Nomenclature section.

Uncertainty in biomass feedstock supply, leading to fluctuations in the bioethanol supply chain is the focus of this research. Feedstock supply uncertainty mainly comes from the fluctuation in biomass farm-gate price ($c^{i,t,s}$) and available supply ($b^{i,t,s}$), and both are influenced by natural and social factors. Crop annual yield ($y_c^{i,t}$) and production ($b_c^{i,t}$) are mainly affected by inter-annual weather changes and are the natural factors of spatiotemporal variation. The collectible biomass removal rate (η_c^s) and farmer participation rate (η_p^s) are the two social factors considered in this study because of their uncertainty and subjective influence. The collectible biomass removal rate (η_c^s) represents the proportion of biomass harvested from the field for biomass feedstock. The farmer participation rate (η_p^s) can vary based on environmental and economic considerations.

Corn stover is used as the biomass feedstock because corn is one of the most important crops in the United States. The corn stover harvest index (η_{sh}), corn grain harvest index (η_{gh}) and collectible corn stover removal rate (η_c^s) are introduced to capture the proportion of crop residue in the total crop biomass (grain + straw). Then, the county-level corn stover collectible yield ($y^{i,t,s}$) is obtained (Eq. (1)).

$$y^{i,t,s} = y_c^{i,t} \times \frac{\eta_{sh}}{\eta_{gh}} \times \eta_c^s \quad \forall i \in I,\ t \in T,\ s \in S \tag{1}$$

The corn stover farm-gate price ($c^{i,t,s}$) is comprised of corn stover production cost and nutritional compensation cost. The nutritional compensation cost is based on the nutrition removed by each million gram (Mg) of corn stover and assumed to be $24.2 Mg^{-1} [52]. Corn stover production involves four major steps: windrowing, baling, collecting, and in-field transportation [22]. The corn stover production cost changes depending on whether an operation is customized or self-owned, the selection and availability of machinery, fuel and labor prices, land area, crop conditions, and performance characteristics of the machines being operated [53]. The custom rate for windrowing is based on operating acreage, whereas the rates of other three operations are based on the number of rectangular bales [22,53]. The weight of a rectangular bale is in the range of 566–771 kg [54]. In this study, 600 kg is assumed to be the weight of a rectangular bale. The custom rate is $13.4 per acre for windrowing, and the costs of baling, picking, and moving are $14.8, $3.15, and $3.3 for each bale of corn stover, respectively [53]. Yield variations affect not only biomass availability but also windrowing costs. a high corn stover yield reduces the unit collection cost. Therefore, it is hypothesized that the corn stover farm-gate price per unit ($c^{i,t,s}$) consists of the fixed price (cf_{cs}), which is independent of the yield and nutritional compensation cost, and the variable price (cv_{cs}), which is inversely proportional to the corn stover yield (Eq. (2)).

$$c^{i,t,s} = cf_{cs} + \frac{cv_{cs}}{y^{i,t,s}} \forall i \in I,\ t \in T,\ s \in S \tag{2}$$

Annual corn production varies not only with corn yield but also with corn planting area. The amount of corn stover that can be acquired depends on the willingness of the farmer to sell (η_p^s). Hence, corn stover availability ($b^{i,t,s}$) is estimated by the annual corn production volume ($b_c^{i,t}$), corn stover harvest index (η_{sh}), corn grain harvest index (η_{gh}), collectible corn stover removal rate (η_c^s), and farmer participation rate (η_p^s) (Eq. (3)).

$$b^{i,t,s} = b_c^{i,t} \times \frac{\eta_{sh}}{\eta_{gh}} \times \eta_c^s \times \eta_p^s \forall i \in I,\ t \in T,\ s \in S \tag{3}$$

3. Model formulation

3.1. Multiperiod SP model

3.1.1. Objective function

For the multiperiod SP model, the overall expected bioethanol production cost (Z_{SP}) is comprised of four components: biomass purchase cost ($C_P^{t,s}$), transportation cost ($C_T^{t,s}$), CSP cost (C_S^t), and biorefinery cost (C_B^t) (Eq. (4)). CSP and biorefinery-related costs, the first-stage decision variables, do not change in different scenarios or years once decided, whereas biomass purchase and transportation costs related to second-stage decision variables change with different scenarios (ρ^s).

$$Minimize\ Z_{SP} = \sum_t \sum_s \rho^s \times \left(C_P^{t,s} + C_T^{t,s}\right) + \sum_t \left(C_S^t + C_B^t\right) \tag{4}$$

Biomass purchase cost ($C_P^{t,s}$) changes annually in different scenarios. It is a function of the optimal biomass flow pattern ($f^{i,j,t,s}$) from the supply site to the CSP site and the county-level biomass farm-gate price at the supply site ($c^{i,t,s}$) (Eq. (5)).

$$C_P^{t,s} = \sum_i \sum_j c^{i,t,s} \times f^{i,j,t,s}\ \forall t \in T,\ s \in S \tag{5}$$

Biomass transportation cost ($C_T^{t,s}$) is comprised of variable ($C_{T_v}^{t,s}$) and fixed ($C_{T_f}^{t,s}$) transportation costs at period t in scenario s (Eq.

(6)). The variable transportation cost is a function of the unit variable transportation cost (t_{v1}, t_{v2}), the volume of biomass being transported ($f^{i,j,t,s}$ $f^{j,k,t,s}$), and transportation distance ($d^{i,j}$, $d^{j,k}$) including the return route (Eq. (7)). The fixed transportation cost includes the loading and unloading costs, which depend on the unit fixed transportation cost (t_{f1},t_{f2}) and the amount of biomass being transported ($f^{i,j,t,s}$ $f^{j,k,t,s}$) (Eq. (8)). The shortest distances between the facilities within the system ($d^{i,j}$, $d^{j,k}$) are inputs calculated by ArcGIS using the existing road network [14,22]. The transportation cost coefficients before and after pre-processing are summarized in Table A1 in Supplementary data.

$$C_T^{t,s} = C_{T_v}^{t,s} + C_{T_f}^{t,s} \ \forall t \in T, \ s \in S \tag{6}$$

$$C_{T_v}^{t,s} = \sum_i \sum_j \left(t_{v1} \times f^{i,j,t,s} \times d^{i,j} \times 2 \right) + \sum_j \sum_k \left(t_{v2} \times f^{j,k,t,s} \times d^{j,k} \times 2 \right) \ \forall t \in T, \ s \in S \tag{7}$$

$$C_{T_f}^{t,s} = \sum_i \sum_j \left(t_{f1} \times f^{i,j,t,s} \right) + \sum_j \sum_k \left(t_{f2} \times f^{j,k,t,s} \right) \ \forall t \in T, \ s \in S \tag{8}$$

The cost related to CSP facilities (C_S^t) for any period t is composed of the annual operating cost ($C_{S_o}^t$) and annual capital-related cost ($C_{S_c}^t$) (Eq. (9)). In this study, it is assumed that CSP facilities with different capacities incurred the same unit operating cost (s_{op}). Therefore, the annual operating cost is linearly dependent on the demand for biomass at CSP facilities (Eq. (10)). The annual capital cost is linearly dependent on capital investment cost, and factor α is used to represent this relationship [55]. To improve accuracy, the study adopts a piecewise linear approximation to estimate the capital investment cost for three different capacity levels of a facility (Table A.2 and Table A.3 in Supplementary data). Therefore, annual capital-related cost is linearly dependent on the sum of the variable (s_v^l) and fixed (s_f^l) capital-related costs at each level of capacity at each potential location (Eq. (11)). The binary decision variable $o_S^{t,j,l}$ controls the capacity level l of the CSP facility located in county j in year t, and the variable $p^{t,j,l}$ represents the specific capacity of the CSP facility in county j at capacity level l in year t. The detailed piecewise linear approximation equations are provided by Lin et al. (2013) [55].

$$C_S^t = C_{S_o}^t + C_{S_c}^t \ \forall t \in T \tag{9}$$

$$C_{S_o}^t = s_{op} \times \sum_j \sum_l p^{t,j,l} \ \forall t \in T \tag{10}$$

$$C_{S_c}^t = \alpha \times \left(\sum_j \sum_l \left(s_v^l \times p^{t,j,l} + s_f^l \times o_S^{t,j,l} \right) \right) \ \forall t \in T \tag{11}$$

Like CSP facilities, the cost related to a biorefinery (C_B^t) consists of the annual biorefinery operating cost ($C_{B_o}^t$) and annual biorefinery capital cost ($C_{B_c}^t$) (Eqs. 12–14, and a piecewise linear approximation method for elucidating biorefinery capacity is implemented (Table A3 in Supplementary data).

$$C_B^t = C_{B_o}^t + C_{B_c}^t \ \forall t \in T \tag{12}$$

$$C_{B_o}^t = b_{op} \times \sum_k \sum_l q^{t,k,l} \ \forall t \in T \tag{13}$$

$$C_{B_c}^t = \alpha \times \left(\sum_k \sum_l \left(b_v^l \times q^{t,k,l} + b_f^l \times o_B^{t,k,l} \right) \right) \quad \forall t \in T \tag{14}$$

3.1.2. Constraints

The total volume of biomass output from biomass supply site i should not exceed its biomass availability at period t in scenario s (Eq. (15)).

$$\sum_j f^{i,j,t,s} \le b^{i,t,s} \ \forall i \in I, \ t \in T, \ s \in S \tag{15}$$

Considering the mass balance, the CSP capacity in county j should be equal to the total amount of biomass transported to county j from all supply sites i at period t in scenario s (Eq. (16)). The established multiperiod SP model considers the biomass loss at the CSP stage, which affects the biomass flow from CSP facilities to biorefineries ($f^{j,k,t,s}$) (Eq. (17)). The capacity of each CSP facility must be within the corresponding capacity range (Eq. (18)). At most, one capacity level should be chosen for each CSP facility in each county (Eq. (19)). The capacity and location of each CSP facility should be determined in the first year of the planning period (Eqs. (20) and (21)).

$$\sum_i f^{i,j,t,s} = \sum_l p^{t,j,l} \ \forall j \in J, \ t \in T, \ s \in S \tag{16}$$

$$\sum_k f^{j,k,t,s} = \sum_i f^{i,j,t,s} \times (1 - \beta) \quad \forall j \in J, \ t \in T, \ s \in S \tag{17}$$

$$s_{lowcap}^l \times o_S^{t,j,l} \le p^{t,j,l} \le s_{upcap}^l \times o_S^{t,j,l} \quad \forall t \in T, j \in J, \ l \in L \tag{18}$$

$$\sum_l o_S^{t,j,l} \le 1 \quad \forall \ t \in T, j \in J \tag{19}$$

$$\sum_j \sum_l p^{t,j,l} = \sum_j \sum_l p^{1,j,l} \ \forall \ t \in T \tag{20}$$

$$\sum_j \sum_l o_S^{t,j,l} = \sum_j \sum_l o_S^{1,j,l} \ \forall \ t \in T \tag{21}$$

Similarly, the volume of all the preprocessed biomass supplied to a biorefinery located in county k from all CSP facilities at period t in scenario s should be equal to the biorefinery facility capacity (Eq. (22)). The total capacity of all biorefineries should meet the specified demand for the processed biomass feedstock Q_{bf}^t (Eq. (23)). The biorefinery capacity in different areas must be within the corresponding capacity range (Eq. (24)). At each candidate site, there is at most one capacity level of the biorefinery (Eq. (25)). Like those of the CSP facility, the capacity and location of each biorefinery should be determined at the beginning of the planning period (Eqs. (26) and (27)).

$$\sum_j f^{j,k,t,s} = \sum_l q^{t,k,l} \ \forall k \in K, \ t \in T, \ s \in S \tag{22}$$

$$\sum_k \sum_l q^{t,k,l} = Q^t_{bf} \ \forall \ t \in T \tag{23}$$

$$b^l_{lowcap} \times o^{t,k,l}_B \le q^{t,k,l} \le b^l_{upcap} \times o^{t,k,l}_B \quad \forall t \in T, k \in K, \ l \in L \tag{24}$$

$$\sum_l o^{t,k,l}_B \le 1 \ \forall t \in T, k \in K \tag{25}$$

$$\sum_k \sum_l q^{t,k,l} = \sum_k \sum_l q^{1,k,l} \ \forall \ t \in T \tag{26}$$

$$\sum_k \sum_l o^{t,k,l}_B = \sum_k \sum_l o^{1,k,l}_B \ \forall \ t \in T \tag{27}$$

3.2. Multiperiod DP model

The multiperiod DP model is developed by incorporating temporal dimensions to study long-term planning variations [55]. The objective of the DP model is to minimize the total production cost ($Z_{DP,s}$) in the planning period for any given scenario s including ES, comprising the costs of biomass purchase ($C^t_{P,s}$), transportation ($C^t_{T,s}$), CSP (C^t_S), and biorefinery (C^t_B) (Eq. (28)). The DP model cannot incorporate a set of scenarios with assigned probabilities in one analysis simultaneously, and only provides the optimal results for each individual scenario, which could be partially compensated by the DPES model.

$$Minimize \ Z_{DP,s} = \sum_t \left(C^t_{P,s} + C^t_{T,s} + C^t_S + C^t_B \right) \forall s \in S \tag{28}$$

The multiperiod SP and DP models of BSCN are MILPs developed on the Spyder platform using Python 3.7 and solved using Gurobi 9.5.0. Detailed descriptions of the decision variables and parameters are provided in the Nomenclature section.

3.3. Economic assessment indicator

To evaluate the difference in economic benefits between the SP and DPES models when dealing with uncertain information, the expected value with perfect information (EVPI) is used [20]. Here, we quantify the EVPI of the SP model as the expected difference between the objective value from the SP and DP models for each scenario (Eq. (29)), as well the EVPI of the DPES model (Eq. (30)).

$$EVPI_{SP} = \sum_{s \in S} \rho^s \times \left(Z^s_{SP} - Z_{DP,s} \right) \tag{29}$$

$$EVPI_{DPES} = \sum_{s \in S} \rho^s \times \left(Z^s_{DPES} - Z_{DP,s} \right) \tag{30}$$

where, Z^s_{SP} represents the total cost of the BSCN when the input parameters corresponding to scenario s are adopted under the strategic variables predetermined by the SP model; $Z_{DP,s}$ represents the total cost of the BSCN obtained by the DP model for any individual scenario s; Z^s_{DPES} represents the total cost of the BSCN when the input parameters corresponding to scenario s are adopted under the strategic variables predetermined by the DPES model; ρ^s is the scenario probability.

4. Case study

4.1. Site description

Feedstock availability and procurement price changing spatiotemporally are critical factors for planning a BSCN. In this study, corn stover is considered as the biomass feedstock. The state of Illinois, one of the most important corn producers in the US Corn Belt, is chosen to study the long-term planning of BSCN. A 10-year period (2007–2016) is used to develop the multiperiod SP and DPES models, and a 3-year period (2017, 2018 and 2020) is used to validate the rationality of the spatial distribution and economic performance of the SP- and DPES-based BSCNs. However, it should be emphasized that the developed programming models are not specific for corn stover-to-bioethanol production but can be adapted to other types of biomass feedstock in any other region, where there is full biomass feedstock and a huge demand for biofuel production and consumption. All 102 counties in Illinois are considered candidate locations for biomass supply, CSP facilities, and biorefinery sites. The ethanol demand for all scenarios is assumed to be constant at 100 million gallons/yr. Then, the annual demand for corn stover at the biorefinery gate is estimated at 1.25 million Mg, assuming an ethanol conversion rate of 80 gallons/Mg [20,41]. The biomass loss rate during CSP is set at 5% [55], and the corn stover harvest index (η_{sh}) and corn grain harvest index (η_{gh}) are both assumed to be 0.5, which implies that corn stover dry matter yield is equal to corn grain yield [51,56].

County-level corn yield and production data for 2007–2018 and 2020 are obtained from the United States Department of Agriculture National Agricultural Statistics Service' Quick Stats database (https://quickstats.nass.usda.gov/) (Figs. A1 and A.2 in Supplementary data) and are used to estimate corn stover yield and production at the county level. It should be noted that data for some counties were missing in some years, and the counties with more than three years of missing data during the 13 years were dropped. For counties missing one or two years of data, missing data were interpolated using adjacent years and counties with available data. Finally, we end up with complete data for 95 of the 102 counties of Illinois over the 13-year period (2007–2018 and 2020). Corn yields and productions in the seven missing counties have historically been low, and therefore their omission will have minimal impact on the corn stover-to-bioethanol supply chain in this research. In addition, the year 2019 was excluded because corn production and yield data from 24 counties were missing in that year.

Historical corn data indicate that both corn yield and production change annually. The average corn yield in Illinois varied from a minimum of 1.98 Mg/acre in 2012 to a maximum of 4.36 Mg/acre in 2018; the total corn production volume varied from 28.3 million Mg in 2012 to 50.0 million Mg in 2014 (Fig. 2). A drought in 2012 is assumed to be the reason for the lowest corn yield and production in the study period [57].

4.2. Scenario setting

In the present study, the two independent uncertain parameters, collectible corn stover removal rate and farmer participation rate, are assumed to follow normal distributions, and their value intervals are determined based on the survey results from Iowa (Table 2), considering that Iowa and Illinois are the major corn producers of the US Corn Belt and are geographically contiguous [51,58]. For the distribution intervals of collectible corn stover removal rate and farmer participation rate, 20 and 12 discrete scenarios are selected, respectively, and their discrete scenario distributions of the two uncertain parameters are incorporated to generate the combined biomass supply distribution with a total of

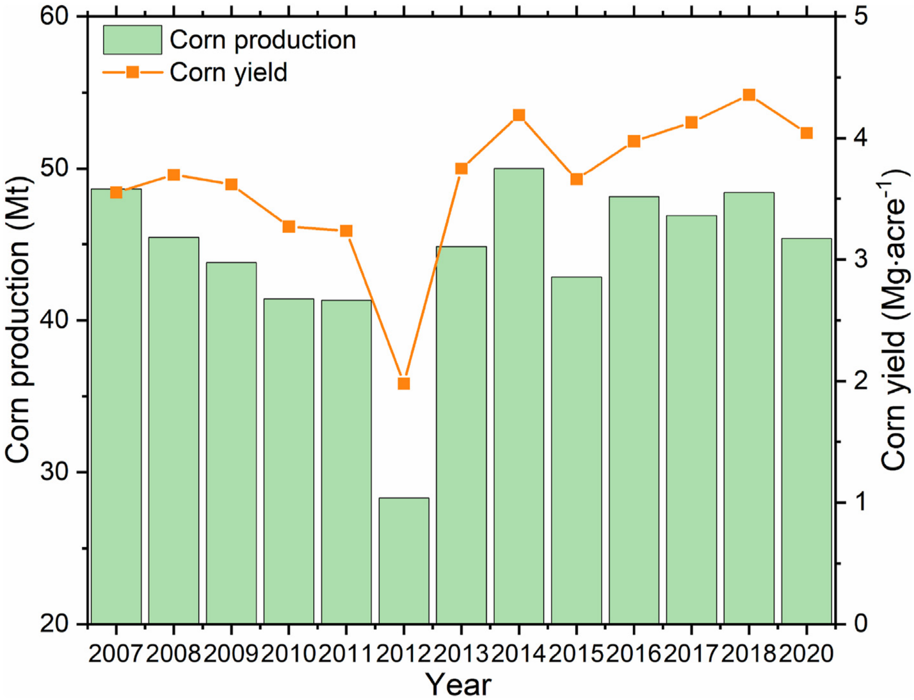

Fig. 2. Illinois corn yield and production during 2007–2018 and 2020. The data from 2007 to 2016 are applied to develop the biomass-to-bioethanol supply chain network (BSCN) by stochastic programming (SP) and deterministic programming for the expected scenario (DPES), and the data for 2017, 2018 and 2020 are used to validate the economic performance of the developed BSCNs based on the SP and DPES models.

Table 2
Scenario distribution of uncertain parameters.

Uncertain parameter	Distribution	Interval	Scenarios
Collectible corn stover removal rate	η_c^s ~ N (0.5, 0.2)	0.3–0.7	20
Farmer participation rate	η_p^s ~ N (0.36, 0.12)	0.24–0.48	12

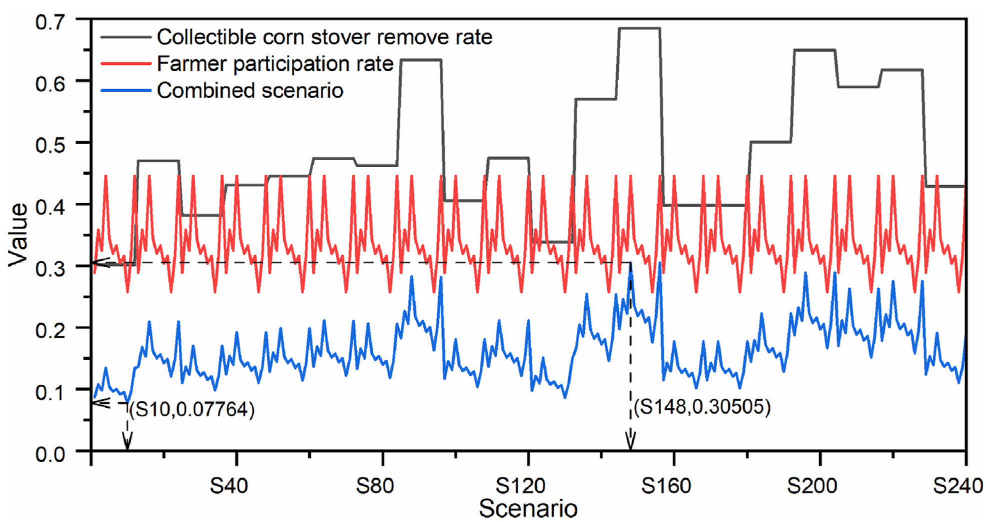

Fig. 3. Value distributions of uncertain parameters and their combined scenarios with a total of 240 based on the assumption that the scenario values of uncertain parameters follow normal distributions and the probability of their combined scenarios follows a uniform distribution.

240 scenarios, whose probability follows a uniform distribution (Fig. 3). The minimum and maximum combined values appear in scenarios 10 (S10) and 148 (S148), respectively. According to the probability distribution of the 240 scenarios, the values of the collectible corn stover removal rate and farmer participation rate of ES are calculated to be 0.483 and 0.338, respectively.

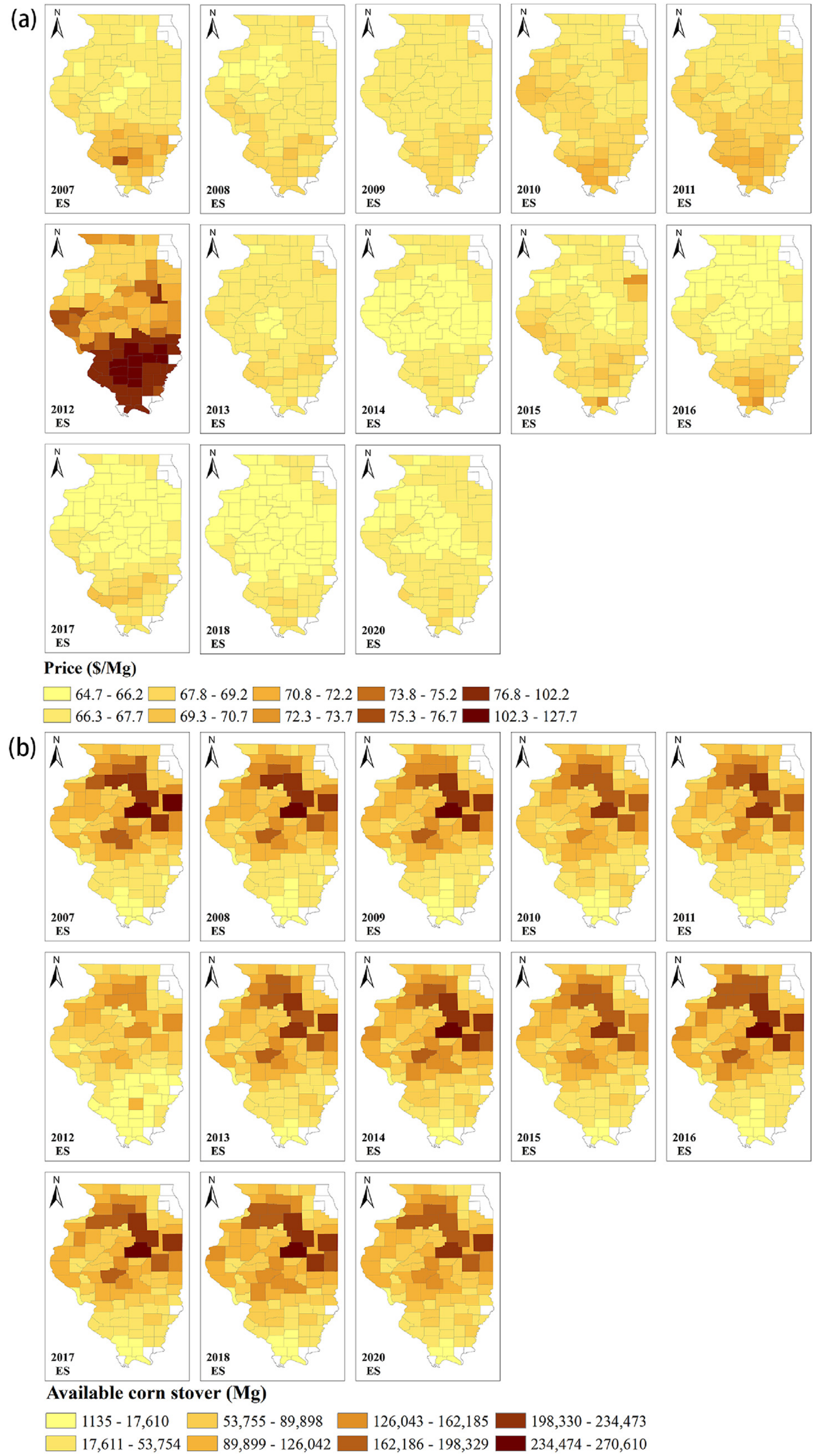

Fig. 4. County-level farm-gate price (a) and available supply (b) of corn stover for the expected scenario (ES) with collectible corn stover removal rate $\eta_c^s = 0.483$ and farmer participation rate $\eta_p^s = 0.338$ during 2007–2018 and 2020.

Table 3
Locations of centralized storage and preprocessing (CSP) and biorefinery facilities optimized by two different programming models.

Model	CSP facility	Biorefinery
SP	McLean	McLean
DPES	Lee; La Salle	Lee

4.3. Spatiotemporal distribution of corn stover farm-gate price and available supply

The county-level farm-gate price and available supply distribution of corn stover in different years are obtained according to the corn field and production data and the conversion formulas

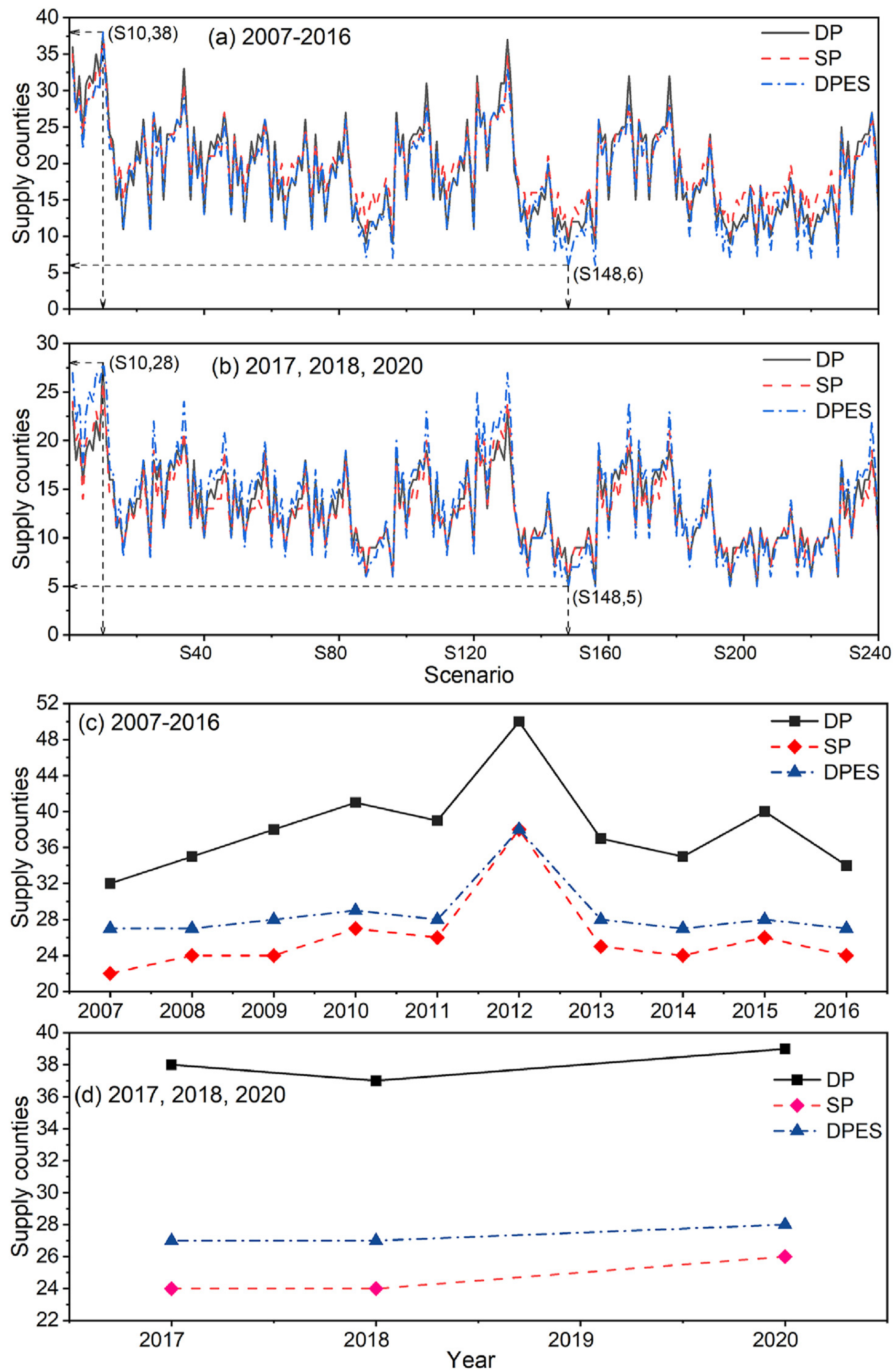

Fig. 5. Annual variation in the number of supply counties across scenarios under the multiperiod stochastic programming (SP) and deterministic programming for the expected scenario (DPES) models in the model development period of 2007–2016 (a) and the model validation period of 2017, 2018 and 2020 (b), and the scenario-expected variation in the number of supply counties across years under the multiperiod SP and DPES models in the development (c) and validation periods (d). The variations in the number of supply counties under the separate DP models developed for each scenario independently in the model development period and the model validation period are the benchmark.

(Eqs. (1)–(3)). The biomass farm-gate price is related to the collectible corn stover yield (Eq. (2)), which is related to the collectible corn stover removal rate (Eq. (1)). The farm-gate price for ES with collectible corn stover removal rate $\eta_c^s = 0.483$ is presented in Fig. 4a. The distribution of low-value areas of farm-gate prices is similar to that of high-value areas of corn yield (Fig. A1 in Supplementary data) and is concentrated in the central and northern counties. The lowest yield in 2012 resulted in the highest farm-gate price distribution during the 13-year period (Fig. 4a). The available supply distribution of corn stover is closely related to the annual corn production (Eq. (3)) and is affected by the collectible corn stover removal rate (η_c^s) and farmer participation rate (η_p^s). In general, the spatiotemporal distributions of corn production and corn stover availability are similar (Fig. A2 in Supplementary data). High-value regions are mainly concentrated in the central and northern counties, while the southern region maintains relatively low value throughout the 13-year period (Fig. 4b). The most productive county of corn stover fluctuates between McLean, Livingston, Iroquois, La Salle, and Bureau counties (Fig. 4b). The distribution of corn stover farm-gate price and available supply implies that the optimal BSCN may be in the central to northern counties due to the lower biomass feedstock purchase and higher feedstock supply. The spatiotemporal distributions of the farm-gate price and available supply of corn stover for the other scenarios are like those for ES, except for differences in specific values.

5. Results and discussion

5.1. Spatiotemporal distribution of the SP- and DPES-based BSCNs

5.1.1. Facility location and supply county

The preferred facility locations optimized by the two types of programming models are different (Table 3). Considering the variations in the 240 scenarios, the SP model chooses to develop one CSP facility and one biorefinery in the BSCN, which are always located in McLean. However, under the DPES model, two CSP facilities are recommended to preprocess biomass feedstock locally for the reduction of biomass transportation cost, and one medium-level biorefinery facility is suggested to achieve economies of scale.

The annual number of supply counties across different scenarios under the SP and DPES models show similar change trends in the 10-year development period (2007–2016) and the 3-year validation period (2017, 2018 and 2020) (Fig. 5a and b). The selection of SP and DPES supply counties in the 3-year validation period is based on the facility locations and capacities predetermined by the SP and DPES models in the 10-year development period, respectively (Table 3). However, as the reference benchmark, separate DP models were developed for each scenario, with a total of 240 scenarios, independently in the two periods. The number of supply counties required in the SP and DPES models to meet biomass demand range from 10 to 38 and 6 to 38, respectively, during the 10-year development period of 2007–2016 (Fig. 5a). Based on the developed CSP and biorefinery facilities, the number of supply counties in the validation period of 2017–2018 and 2020 under the SP and DPES models range from 6 to 26 and 5 to 28, respectively, across the 240 scenarios (Fig. 5b). The variation curves of the supply counties of the two models are similar (Fig. 5a and b); they are opposite to that of the combined values of the two studied uncertain parameters (Fig. 3). The scenario of maximum and minimum supply counties in the two periods (2007–2016; 2017, 2018, and 2020) corresponds to that of minimum and maximum combined distribution values (i.e., S10 and S148), respectively. The decreased number of biomass supply counties results from the increased collectible corn stover removal and farmer participation rates, which can improve the stability of BSCN and reduce the transportation distance and cost.

The scenario-expected variation in the number of supply counties across different years shows that there is an abnormal increase in 2012 attributed to the sharp drop in corn stover availability due to severe drought, potentially leading to an increase in total cost due to the increased transportation distance and cost (Fig. 5c and d). Because the fluctuations in yield and production are relatively gentle in most years of the 13-year period (Fig. 2), the quantity fluctuation in supply counties over the study period under any programming model is small, especially in the 3-year validation period (Fig. 5c and d). The high number of supply counties under the DP model mainly results from that the BSCN is optimized separately for each scenario in any year, whose strategic and tactical variables could vary across Illinois state, while the strategic variables under the SP and DPES models could not change with scenario or year once they are determined and the supply counties could only be distributed around them given the cost constraints. The optimal biomass supply counties and related transportation distances vary with year because of the yearly variated biomass yield and supply availability, affecting the biomass farm-gate price and transportation cost, and finally resulting in the variation of the total cost of the developed BSCN.

5.1.2. Spatiotemporal variation

The BSCN under the SP model shows a much better geospatial distribution than that under the DPES model for both periods (Fig. 6). The statistical results of the separate DP models developed for each scenario show that the optimal locations of supply counties and facilities vary dramatically across scenarios and periods (Fig. 6a and d). Of the 240 scenarios optimized in the 10-year development period, Lee, La Salle, McLean, and Champaign are the most frequently identified counties for facility sites annually (Fig. 6a). The optimal supply county locations are located mainly around these facilities. The central region around McLean and the northern region around Lee are both competitively positioned as the best distribution areas for BSCN (Fig. 6a), leading to that the spatial distribution of BSCN under the SP model (Fig. 6b) and that under the DPES model (Fig. 6c) are equally reasonable.

However, in the 3-year validation period, the spatial distribution of BSCN under the SP model exhibited much better rationality than that under the DPES model (Fig. 6d–f). The best candidate locations for facilities and supply counties are most frequently identified in the central region, mainly in McLean and Macon, based on the statistical results of the separate DP models developed for each scenario in the 3-year validation period (Fig. 6d), which are much more similar to the spatial distribution of BSCN under the SP model (Fig. 6e). The large difference between the spatial distribution of BSCN under the DPES model (Fig. 6f) and the ideal distribution of BSCN (Fig. 6d) implies that the total cost of the BSCN under the DPES model is much higher than that under the SP model in the validation period. The results show that the strategic variables determined by the multiperiod SP model have stronger temporal robustness than those determined by the DPES model.

The dramatic variation in the strategic variables of the separate DP model developed for each scenario is not conducive to investment returns, particularly to infrastructure investment requiring a long payback period (Fig. 6a and d). It is difficult to determine the optimal location and capacity of strategic variables according to the statistical results of DP conducted 240 times separately. The supply chain optimization is conducted independently in the development period and the validation period under the DP model with no predetermined decision variables, which is different from that in the validation period under the SP and DPES models. The is because the core of this study is to compare the rationality of the optimized

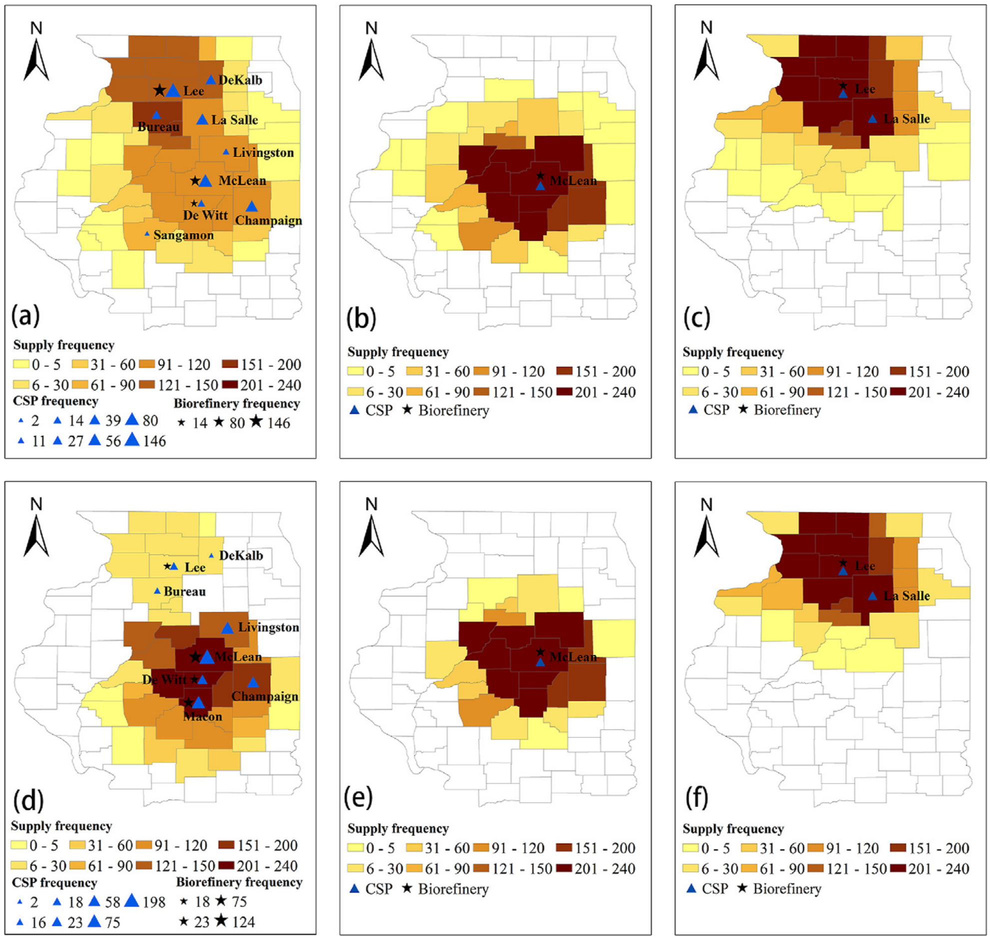

Fig. 6. Annual frequency of supply county, centralized storage and preprocessing (CSP), and biorefinery under the separate deterministic programming (DP) model developed for each scenario independently in the 10-year model development period and 3-year model validation period (a and d); annual frequency of supply county, CSP, and biorefinery in the 10-year model development period under the stochastic programming (SP) and deterministic programming for the expected scenario (DPES) models (b and c); and annual frequency of supply county in the 3-year model validation period with the predetermined strategic variables optimized by the SP and DPES models in the 10-year model development period (e and f).

strategic variables and the accompanying economic performance between the SP and DPES models, both of which are based on the statistical results of the separate DP model developed for each scenario in different periods (Eqs. (29) and (30)).

5.2. Biofuel production cost of the SP- and DPES-based BSCNs

The difference in annual bioethanol production cost of BSCN for different scenarios indicates that the cost of the SP-based BSCN is closer to the theoretical minimum values statistically determined by the DP models for each scenario than that of the DPES-based BSCN in both periods (Fig. 7). The annual cost differences between the DPES and DP models are higher than that between the SP and DP models for most scenarios, which is more obvious in the validation period (Fig. 7b). The general variation trends in the annual cost curves of the three models (Fig. A4 in Supplementary data) agree with those of the supply counties (Fig. 5) and opposite to that of combined scenario values (Fig. 3). The maximum and minimum annual BSCN costs determined by the three programming methods in the two periods are presented in S10 and S148, respectively, corresponding to the minimum and maximum values of the combined scenarios (Fig. 3).

The expected annual costs for all scenarios obtained by the SP model are smaller than those obtained by the DPES model, both in the model development and validation periods (Table 4). Based on an annual bioethanol demand of 100 million gallons, the annual cost saving by the SP model is $0.25 million/yr in the 10-year development period compared to the bioethanol production cost determined by the DPES model. The strategic variables determined by the SP model show much better spatial rationality (Fig. 6e) and economic superiority (Table 4) in the 3-year validation period. An annual cost saving of $1.22 million/yr is achieved by the SP model compared to the bioethanol production cost determined by the DPES model. The SP-based BSCN in the validation period explains the much higher cost savings. Meanwhile, as a measurement indicator, a lower EVPI implies that the SP model exhibits less sensitivity to imperfect information and less dependence on the complete knowledge of future decisions both in the model development and validation periods, indicating its greater robustness than the DPES model.

5.3. SP-based BSCN cost breakdown

5.3.1. Scenario-based cost breakdown

The SP results indicate that the annual expected bioethanol production cost is $281.29 million/yr in the 10-year model development period. The biorefinery cost ($140.76 million/yr) accounts for almost half of the bioethanol production cost, followed by

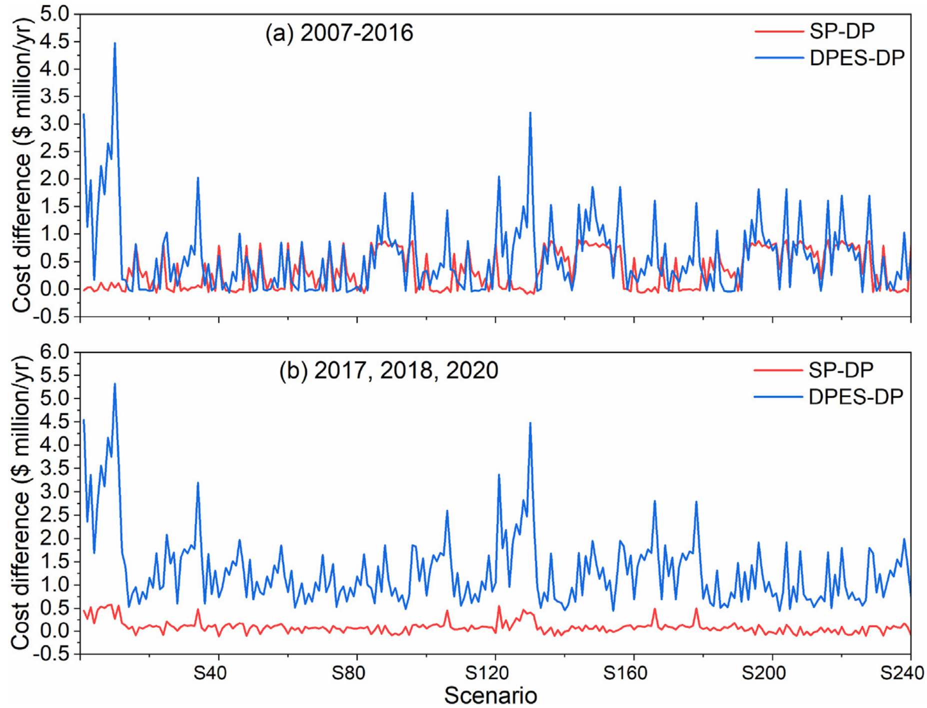

Fig. 7. Annual bioethanol production cost difference between the supply chain under the separate deterministic programming (DP) model developed for each scenario, and stochastic programming (SP) and deterministic programming for the expected scenario (DPES) models in model development period (a) and validation period (b).

Table 4
Bioethanol production cost differences between the stochastic programming (SP) and deterministic programming for the expected scenario (DPES) models.

Period	Model	Expected cost /$ million/yr	EVPI /$ million/yr
Model development period	SP	281.29	0.34
	DPES	281.54	0.59
Model validation period	SP	278.56	0.09
	DPES	279.78	1.31

EVPI represents the expected value with perfect information.

biomass purchase cost ($88.51 million/yr), transportation cost ($34.86 million/yr), and CSP cost ($17.15 million/yr). The annual bioethanol production cost varies from $298.75 million/yr to $269.38 million/yr in different scenarios (Fig. 8a). The annual biomass purchase cost and transportation cost are the major contributors to the variation of bioethanol production cost, which varies from $93.89 million/yr to $85.17 million/yr and from $46.96 million/yr to $26.30 million/yr, respectively. These reductions are attributed to the lower farm-gate price and shorter transport distance resulting from increased biomass availability and decreased number of biomass-supplying counties (Fig. 5a). As shown in Fig. 8b, the proportion of biomass purchase cost to bioethanol production cost ranges from 32.5% to 30.9%, and the transportation cost percentage ranges from 15.7% to 9.8%. The proportion changes in biorefinery cost (47.1%–52.3%) and CSP cost (5.7%–6.4%) result from the fact that the costs of these strategic variables remain constant relative to the changing total cost. Fig. 8c displays the relative variation rate of each component cost relative to the expected component cost. Transportation cost is the most sensitive component to changes in collectible corn stover removal and farmer participation rates across the scenarios. The fluctuation curve of the variation rate in transportation cost maintains a high degree of positive consistency with that of the number of supply counties (Fig. 5a) and a negative consistency with that of the combined scenario value (Fig. 3). The bioethanol production and biomass purchase costs are less sensitive to different scenarios compared to the transportation cost, and the variation rate of the bioethanol production cost is largely consistent with that of the biomass purchase cost, although the transportation cost changes dramatically across scenarios, which can be attributed to the fact that the proportion of transportation cost to total cost (15.7%–9.8%) is much lower than the proportion of biomass purchase cost to total cost (32.5%–30.9%). Owing to their constant values, the variation rates of CSP and biorefinery costs are always going to be 1.

The fluctuations in component cost, percentage, and variation rate in the 3-year model validation period (Fig. 8d–f) are similar to those in the 10-year model development period (Fig. 8a–c). The annual expected bioethanol production cost reaches $278.56 million/yr during the validation period, which is slightly lower than that in the development period due to the higher average yield and production in the validation period (Fig. 2). Transportation cost is the most sensitive variable under different scenarios or uncertain factors.

5.3.2. Year-based cost breakdown

The annual average bioethanol production cost varies from $277.25 million/yr in 2014 to $295.11 million/yr in 2012 in the 10-year model development period (Fig. 9a). The annual changes in corn stover availability affect tactical decisions regarding the optimal number of supply counties and transportation patterns, potentially influencing procurement and transportation costs. The lowest production cost observed in 2014 is attributable to the highest feedstock supply (Fig. 2) and lowest purchase price (Fig. 4) in the central counties of Illinois for supplying corn stover (Fig. 6b and e), and lower transportation cost resulting from a tighter distribution of supply counties (Fig. 5c). The drought in 2012 reduces corn stover availability in each county, leading to increases in both biomass purchase price (Fig. 4) and transportation cost as the

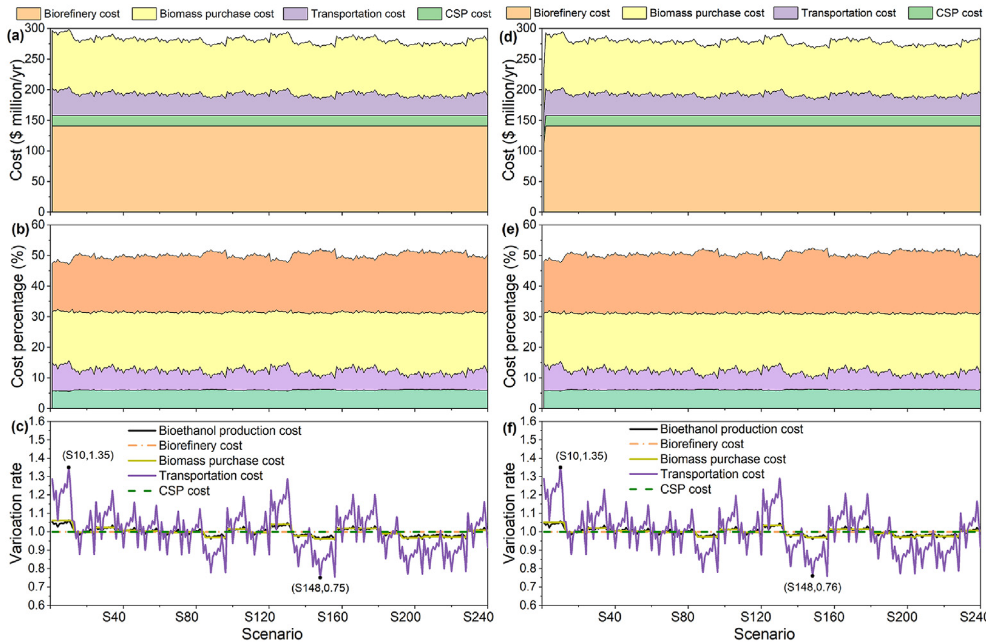

Fig. 8. The cost breakdown, percentage, and variation rate in supply chain in the 10-year model development period of 2007–2016 (a, b and c) and those in the 3-year model validation period of 2017, 2018 and 2020 (d, e and f) across scenarios under the multiperiod stochastic programming model. CSP: centralized storage and preprocessing. Variation rate is calculated as the ratio of the component cost for each scenario to the expected component cost for all 240 scenarios.

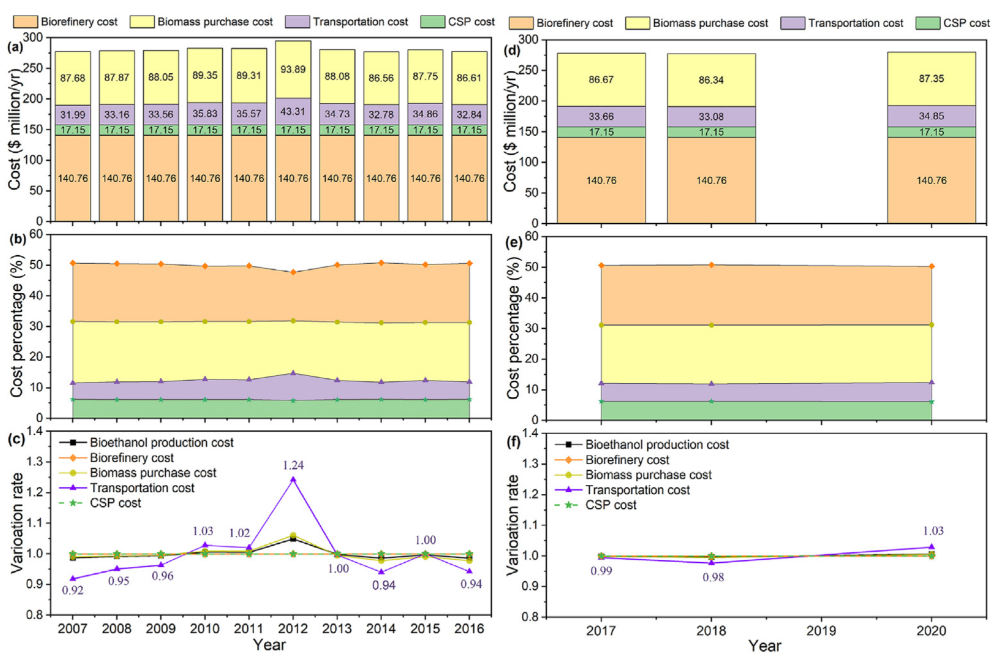

Fig. 9. The cost breakdown, percentage, and variation rate in supply chain in the 10-year model development period of 2007–2016 (a, b and c) and those in the 3-year model validation period of 2017, 2018, and 2020 (d, e and f) across years under the multiperiod stochastic programming model. CSP: centralized storage and preprocessing. Variation rate is calculated as the ratio of the cost for each year to the average cost throughout the calculated period.

number of supply counties soared (Fig. 5c). The peak variation rate of transportation cost in 2012 (1.24) implies that the transportation cost is the most sensitive component for variation in natural weather and feedstock production compared to other components (Fig. 9c). However, the variation rate of the bioethanol production cost is mainly in agreement with that of the biomass purchase cost due to much higher proportion of biomass purchase cost (31.2%–31.8%) than that of transportation cost (11.5%–14.7%) (Fig. 9b), along with the constant costs of strategic variables (Fig. 9a).

The fluctuation in each cost component in the 3-year model validation period is relatively flat (Fig. 9d–f), which is attributed to the stable corn yield and production during this period (Fig. 2). Due to the high and stable yield and production of corn stover, the total costs in the 3-year validation period were lower ($277.33 million/yr–$280.12 million/yr) than those in the model development period of 2007–2016 ($277.25 million/yr–$295.11 million/yr).

The general variation trend of cost breakdown across scenarios and years under the multiperiod DPES model (Fig. A5 and A6 in Supplementary data) are similar to those under the multiperiod SP model. The annual bioethanol production cost decreases from S10 to S148 with increasing biomass supply during both the development and validation periods. In the development period, although the CSP facility cost is $0.47 million/yr higher under the DPES model with two CSP facilities than that under the SP model with one CSP facility because of the lower economy of scale, the distributed CSP facilities lead to an average saving of $0.13 million/yr transportation cost and $0.09 million/yr biomass purchase cost compared to that under the SP model; thus, the total bioethanol production cost under the DPES model ($281.54 million/yr) is $0.25 million/yr higher than that under the SP model ($281.29 million/yr). However, in the validation period, based on the constant higher CSP cost ($0.47 million/yr) under the DPES model and the more reasonable geospatial distribution of BSCN under the SP model (Fig. 6e and f), the biomass purchase and transportation costs of the BSCN under the DPES model are $0.38 million/yr and $0.37 million/yr higher, respectively, than those under the SP model, thus, resulting in the total cost under the DPES model being $1.22 million/yr higher than that under the SP model (Table 4).

6. Conclusions and future researches

A multiperiod SP model is developed as a decision-making method to design a long-term BSCN with uncertainty in biomass supplies because of natural and social fluctuations. The results of the developed model are compared with those of the DPES model in the model development period and the model validation period, taking the statistical results of the separate DP model developed for each uncertain scenario as a benchmark. The optimization objective is to minimize the expected cost of bioethanol production. The strategic variables of the SP and DPES models do not change with scenario or year in the two periods, while the tactical variables fluctuate under both the SP and DPES models. The optimization results of the SP model were comparable to those of the DPES model in the model development period owing to the reasonable geospatial distribution of BSCN. However, in the model validation period, the SP model exhibits a more reasonable geospatial distribution and much better economic performance than the DPES model. The lower expected cost and EVPI demonstrate that the SP model is less sensitive to imperfect information and has stronger robustness to possible natural and social fluctuations in multi-year planning. The biorefinery cost is the most important component of the total bioethanol production cost. Transportation cost, followed by biomass purchase cost, is the most sensitive component for assessing changes in collectible corn stover removal and farmer participation rates. However, the variation rate for the bioethanol production cost is largely in line with that of the biomass purchase cost, accounting for a larger proportion of biomass purchase cost (30.7%–32.5%) and relatively constant costs of the strategic variables. Compared to the SP model, the DPES model cannot make up for the loss of economy of scale caused by decentralized facility construction although the construction of two CSP facilities can reduce the costs of biomass transportation and procurement.

There are several improvements of this study needed to be conducted in the future. One improvement is that the supply chain scope should be extended to the biofuel consumption stage. A complete commercial pathway is important for commercial use or policy support of biofuels. Besides, seasonal fluctuations in biomass supply and storage should be integrated into the currently established multi-year SP model. The seasonal supply of biomass feedstock, especially crop residues, would lead to integrated strategic and tactical management of the biomass supply chain. Finally, longer and more variable validation periods are needed to compare the performance of the SP and DPES models.

CRediT authorship contribution statement

Changqiang Guo: Conceptualization, Methodology, Programming, Formal analysis, Writing – original draft. **Hao Hu:** Conceptualization, Data curation, Methodology, Programming. **Shaowen Wang:** Conceptualization, Interpretation, Validation. **Luis F. Rodriguez:** Conceptualization, Methodology, Data curation. **K.C. Ting:** Methodology, Data curation, Writing – review & editing. **Tao Lin:** Conceptualization, Data curation, Methodology, Supervision, Writing – review & editing.

Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.renene.2021.12.144.

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