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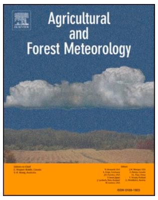

Review

A bibliometric analysis on drought and heat indices in agriculture

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ABSTRACT

Under the ongoing global warming, drought and heat extreme events are increasing in frequency and intensity. While adversely affecting the environment, these changes will have inevitable socioeconomic consequences. By combining bibliometric science mapping and break-point analyses to synthetize the global research published on drought and heat indices applied in agriculture in the 1950–2022 period, the present study provides a first comprehensive view of this research theme. Bibliometric analyses were applied to a set of 4,948 scientific publications retrieved from the Elsevier's Scopus and the Web of Science databases. The results identified 5 different research fields of applications of these indices concerning drought analysis at different time scales, climate change risk, drought effects at crop/plant level, water resource management and drought monitoring from remote sensing. Through a break-point analysis, three sub-periods of scientific literature were identified with different publication rate and the main changes in research interest were highlighted.

A total of 124 drought and 20 heat indices reported in the bibliographic dataset were detected and analyzed in terms of number of occurrences and research impact. The most utilized indices are SPI and CWSI, both drought-related, but their research impact is currently overcome by other indices such as, for example, SSWI, MIDI and OSAVI, mainly based on remote sensing data. Furthermore, this study showed a change of focus from crop/field to large scale, over the assessed period, also due to the availability of new data sources mainly derived from remote sensing, together with an increasing weight of terms like impact, climate change, scenario, and trend, which highlights the need to address these challenges from a global perspective.

1. Introduction

The ongoing climate change poses ever new challenges worldwide, in many different sectors. The increasing frequency and intensity of extreme weather events, like droughts, wildfires, terrestrial and marine heatwaves, cyclones and floods, have led to widespread damages to human and natural systems (FAO, 2020; IPCC, 2022). Growing detrimental impacts have been observed on ecosystems and ecosystem services, water and food security, socioeconomics resources, and culture (IPCC, 2022). Agricultural systems are among the most vulnerable to climate change (Neset et al., 2019; Raza et al., 2019). The predicted increase in the frequency of droughts, heavy rains and high temperatures, as well as other abiotic stresses (soil salinity and heavy metal contamination), will often be matched by an increase in pests and disease occurrence, resulting in augmented risks of famine (Dhankher and Foyer, 2018). Food security risks are expected to grow in the future in terms of both severity and extensivity due to the increasing global warming (O'Neill et al., 2022). Overall, the severity of impacts from extreme heat and drought tripled in the last 50 years in Europe (IPCC, 2022).

Drought is an important growth-limiting factor for many rain-fed crops and can adversely affect their development (Trabelsi et al., 2019). The highest drought-induced yield losses are observed for legumes and root and/or tuber crops (Daryanto et al., 2017). High temperatures cause heat stress in several crops, with negative effects on plant growth and development that vary with crops (Kaushal et al., 2016; Teixeira et al., 2013). Moreover, response of crops to these stresses depends on development stage, with reproductive phases being more sensitive than vegetative phases (Daryanto et al., 2017; Hatfield and Prueger, 2015; Wardlaw, 1994). On a global scale, heat stress plays a role as important as drought for crop yield losses (Zampieri et al., 2017) and imposes an increasing risk to agricultural production, particularly in continental areas at mid and high Northern latitudes (Teixeira et al., 2013).

The 2003 European heatwave led to a general reduction of 30% in gross primary productivity due to water stress (hereinafter used with the

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same meaning of drought stress) and extreme summer heat in eastern and western Europe, respectively (Ciais et al., 2005). Peaks of high temperature, even when occurring for just a few hours, can drastically reduce the production of important food crops (Porter and Semenov, 2005; Vara Prasad et al., 2000).

Drought is also often associated to heat waves or thermal extremes which can lead to further crop damages. Recent studies suggest that these two stressors can act additively as yield losses are enhanced when drought and high temperature occur simultaneously (Cohen et al., 2021b; Mahrookashani et al., 2017; Mittler, 2006; Sinha et al., 2021; Suzuki et al., 2014). For cereal and legume rain-fed crops, the main cause of yield losses is thought to be the impact of a combination of heat and water-deficit on their reproductive processes (Sinha et al., 2021).

Understanding the phenomena in progress and identifying their spatial and temporal dimension and their evolution is essential for the development of adequate policies and management strategies capable of implementing timely interventions. For this purpose, several indices have been proposed over time, some of a more general value, others targeted at specific aspects. For drought, a review of the mostly used indicators/indices has been published by the WMO (WMO and GWP, 2016), while for thermal extremes, several indices were proposed by the ETCCDI (Klein Tank et al., 2009).

It should be noted that there is not a general agreement about the distinction between the two terms “index” and “indicator” and they are often used as synonyms in literature. An indicator is a function which associates an observable variable with a theoretical variable, but the use of the term indicator is often misleading, because, in many cases, it refers only to the observable variables rather than to the whole function (Hinkel, 2011). In general, indicators are based on simple functions, while more complex functions are adopted for indices. The most shared point is in fact that indices derive from an aggregation of indicators in an increasing concentration of information where data are the basic components of an indicator and multiple indicators are aggregated into indices as described by the indicator pyramid proposed by Braat (1991). Several studies adopted this definition (Joung et al., 2013; Mitchell et al., 1995; Perotto et al., 2008; WMO and GWP, 2016). Yet, indices are defined as indicators, whose value is calculated and compared against a standard (Rivington et al., 2013). However, several indices (e.g. most ETCCDI indices) are not derived from aggregation of multiple variables or indicators (Klein Tank et al., 2009), while for some indicators the opposite occurs (such as the Combined Drought Indicator in WMO and GWP, 2016). For these reasons, hereinafter we will use the term “indices” to refer to both indicators and indices.

Besides the meteorological hazards, other indices have been developed for assessing plant/crops responses to abiotic stress. For heat stress, bioclimatic indices are based on crop specific thresholds which can cause yield losses (Teixeira et al., 2013). Crop stress indices have also been developed for both drought and heat in wheat breeding programmes (Mamrutha et al., 2020).

The simultaneous occurrence of drought and heat conditions could impact agricultural systems to a greater extent than do individual events, and specific compound indices are required for better analyzing such situations. These indices enable to monitor the main climate changes taking place and provide useful information for the choice of crops and cultivation techniques on the one hand, and the definition of adaptive interventions to mitigate their impacts on the other.

The need to describe complex phenomenon requires an increasing complexity of functions applied, from simple to compound/composite indices, up to process-based models which are used to quantify the relationships between weather and yield and their interaction with plant characteristics (Lobell et al., 2013; Challinor et al., 2007; Ruiz-Vera et al., 2018; Texeira et al., 2013). However, to provide representative results, all these approaches require adequate spatial and temporal calibration on the relevant target (e.g., crop type, climate conditions). In general, while indices are more suitable for global analyses and comparison, process-oriented models may be more accurate for effective impact assessments. However, the latter approach requires proper calibration, which strongly depends on the availability (and quality) of input data.

Considering the wide production of research studies on these themes, bibliometric analyses can be particularly efficient to support researchers in the literature review and identify relevant research topics and trends, highlight research gaps as well as to hypothesize future research trajectories. Bibliometric is an effective quantitative procedure for analyzing global trends in scientific publications, therefore allowing to monitor the development of the investigated field. Based on the analysis of annual publication outputs, publishing journals, countries and institutions, bibliometrics has been applied to analyze trends in scientific research in several scientific fields including, but not limited to, remote sensing, global climate change, GHG emissions reduction (Aleixandre-Tudó et al., 2019; Wang et al., 2014; Wang et al., 2022; Zhao et al., 2023). In recent years, however, traditional bibliometric tools have been applied in concert with more advanced approaches known as science mapping or bibliometric mapping (Karimi and Khalilpour, 2015). Science mapping is a spatial representation of how disciplines, fields, specialties, documents, and authors are related to one another (Small, 1999) and aims at displaying the knowledge structure or determining the temporal evolution in research topics. This approach has been applied to several research fields such as biodiversity (Liu et al., 2011; Tan et al., 2023), Mediterranean forests (Nardi et al., 2016), remote sensing (Badaluddin et al., 2021; Zhang et al., 2017a), precision agriculture (Coulibaly et al., 2022; Pallottino et al., 2018), extreme weather events in agriculture (Cogato et al., 2019), water footprint topic (Sun et al., 2022), climate change vulnerability assessment (Di Matteo et al., 2018; Wang et al., 2014; Yuan and Sun, 2022), climate change and carbon sink (Huang et al., 2020), carbon storage (Karimi and Khalilpour, 2015), climate change adaptation (Kim et al., 2022).

While there are no scientific mapping studies on heat extremes or heat waves monitoring in agriculture, this technique has been applied to research on drought monitoring (Ekundayo et al., 2022; Kchouk et al., 2022; Wang et al., 2022; Yildirim et al., 2022; Yilmaz and Yilmaz, 2021).

A shared result of these studies is the identification of the Standardized Precipitation Index (SPI), which is recommended as drought monitoring index by the World Meteorological Organization since 2009 (Hayes et al., 2011), as the most applied monitoring index during the different periods considered, whereas the Standardized Precipitation Evapotranspiration Index (SPEI) is a trend topic of the most recent years (Ekundayo et al., 2022; Wang et al., 2022; Yildirim et al., 2022).

Despite these earlier studies provided an overview of the drought indices’ literature, they were not targeted at agriculture topics and only considered drought indices, without investigating the links between the application of drought and heat indices. Furthermore, they were mostly based on a single literature database (either Scopus or Web of Science), and on a pre-established list of indices. In addition, some of them lack global perspective, being focused on specific geographical areas (Adisa et al., 2020).

The present work represents an effort to enlarge the analysis, considering both WoS and Scopus databases and using more generic queries aimed to retrieve any index used for these studies. The main objectives were to: (i) provide as complete a framework as possible of the indices used in the literature for monitoring drought and heat extreme events and their effects in agriculture; (ii) identify the main research fields and trends; (iii) verify the association in the literature between drought and heat indices applied in agricultural contexts.

2. Materials and methods

The flowchart in Fig. 1 summarizes the workflow followed in this study. The “Data retrieval” section illustrates how the data collection from two different scientific databases was achieved. The “Data Processing” box describes the quantitative analysis performed through database tools and computation code. Then “Scientific mapping” shows

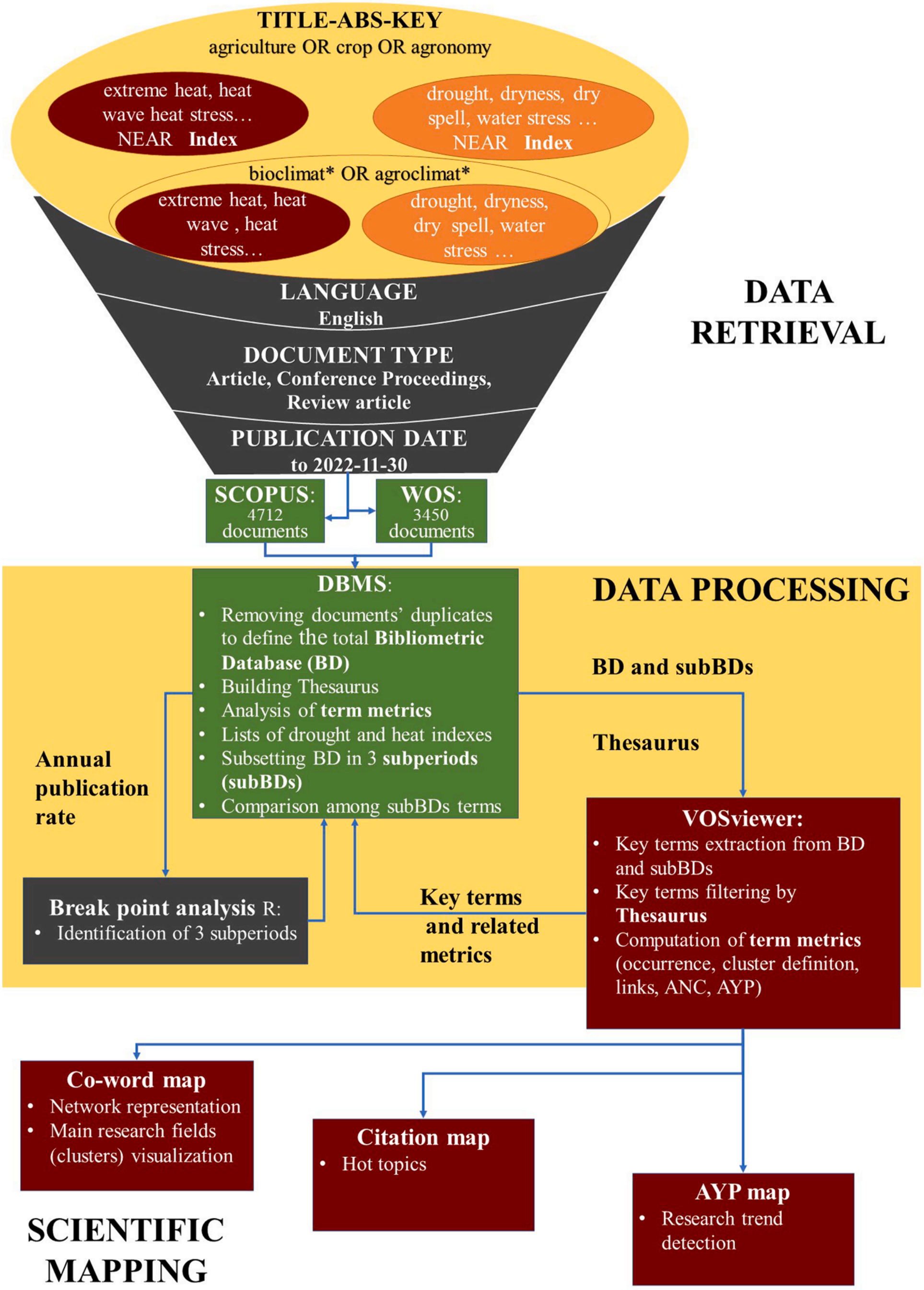

Fig. 1. The workflow for the bibliometric analysis and mapping. AYP: average year of publication; ANC: average normalized number of citations; DBMS: database management system.

how the analysis results were visualized. Details on each section are reported below.

2.1. Data retrieval

The literature search on drought and heat extreme indices was carried out using the two scientific databases Scopus (Elsevier) and Web of Science (WoS) (Clarivate Analytics). Both platforms provide users with specific search tools based on Boolean operators, even though they have different syntax. For example, both databases provide proximity operators, to find words within a certain distance (number of terms) from each other, without specifying a word order. In particular, WoS makes available the *Near/n* operator, which is analogous to the *W/n* operator provided by Scopus. Moreover, the *Pre/n* operator, which also considers the order of the words, is only provided by Scopus. Therefore, to perform the same search in both databases, the query used with Scopus was translated to an analogous query in the WoS language. We retrieved all bibliographic records which reported in the title, abstract, or keywords, fields terms related to (i) agriculture (including *crops* or *agronomy*), (ii) drought or heat extreme either in proximity with the terms index (indexes, indices) or indicator (indicators) or, alternatively, together with terms related to bioclimatic or agroclimatic analyses. The complete query formulation is reported in the Supplementary TabS.1. The search was carried out on 1st December 2022 and was restricted to the articles, reviews and conference papers written in English.

Using the above queries, 4712 and 3450 documents were retrieved from Scopus and WoS, respectively.

2.2. *Data processing*

The two datasets recovered from the WoS and Scopus databases were imported into the Microsoft Access software (Microsoft Corporation, 2022) and organized in a specific database management system (DBMS). Duplicate references were detected based on Digital Object Identifier (DOI), or, in case of missing DOI, on title. Of the retrieved records, 3214 were duplicates, 1498 were downloaded from Scopus only, whereas 236 were exclusively downloaded from WoS, i.e. missing in the Scopus search. After removing duplicates, the total number of publications investigated was 4948 (total Bibliometric Database - BD).

Growth of publications, i.e. number of publications per year, and the top ten active journals were derived from the BD.

To provide additional insights into publication trends and research topic evolution, a break-point analysis was performed by R software version 4.2.1 (R Core Team, 2022) using the package BreakPoints version 1.2 (Hurtado et al., 2020). The Standard Normal Homogeneity Test (SNHT) was used to identify the presence of change points in the publication rate (number of publications per year). A maximum number of two break points with a critical *p-value* equal to 0.1 were set. These change points allowed to subset the BD into sub-Bibliometric Databases (subBDs), corresponding to different sub-periods. The BD and its subBDs were subjected to further bibliometric analyses performed using both the DBMS and a software for scientific mapping, as specified in the following paragraph.

2.3. *Bibliometric mapping*

Bibliographic records retrieved from Scopus and WoS were imported into VOSviewer software version 1.6.18 (van Eck and Waltman, 2010), to produce different co-word maps, also known as term maps. The software was specifically developed for creating, visualizing and exploring sciences' bibliometric maps on VOS (Visualization Of Similarities) mapping technique. The software utilizes natural language processing techniques to extract all terms, i.e. words, occurring in titles and abstracts of publications (van Eck and Waltman, 2011). In a second step, thanks to a linguistic filter, not relevant terms as well as terms occurring in a small number of publications, are automatically excluded by the software.

Using the VOS mapping technique, terms are displayed on the map in a way that the distance between each pair of terms (i.e., i and j) represents their similarity as accurately as possible. The *similarity* among terms (AS_{ij}) considers their number of co-occurrences in the title or abstract counted once per publication, according to the following equation (van Eck and Waltman, 2010):

$$AS_{ij} = \frac{c_{ij}}{w_i w_j}$$

where c_{ij} is the number of publications in which both the terms i and j occur together, while w_i and w_j represent the total number of publications in which the terms i or j appear, respectively.

The larger the number of publications in which two terms co-occur, the stronger the terms are related to each other. Therefore, terms that often co-occur in the same publications are located close to each other in a term map and less strongly related terms (low co-occurrence) are located further away from each other. Each term is represented by a circle, where its diameter and the size of its label indicate the weight, i.e. the number of publications that have the corresponding term in their title or abstract (occurrences).

Once terms were lay out on the map, we used VOSviewer to map clusters of related terms, thus obtaining the so-called word co-occurrence map (hereinafter co-word map). To identify clusters of related terms, the software uses a weighted and parameterized variant of modularity-based clustering, that is the VOS clustering technique (Waltman et al., 2010; Waltman and van Eck, 2013). A cluster can be understood as a research field in which one or more research topics can be identified. The results of this analysis are displayed in the co-word maps as a network of key terms, where terms are represented by labeled circles of different size and color and the strongest links between items are drawn. The area of the circles is proportional to the item weight, as defined above, while the color shows the cluster of membership. Each link represents the connection between two terms derived from the number of publications in which two terms occur together.

Overall, 84,694 terms were extracted by VOSviewer from the BD, of which 7438 terms had at least 4 occurrences. The study focused on this subset of terms, which were filtered based on a specific thesaurus file, created for merging synonyms or different spelled words, ignoring general terms (such "study" or "paper"), and in some cases grouping some too specific terms in larger categories. A thesaurus file associates each term listed with a "replace by" term, which is null in case the original term is to be ignored. The thesaurus was obtained through a process of repeated sessions in which the original list was reduced to a minimum set, after extensive discussions among the authors to reach shared results based on their field experience and a detailed analysis of the literature. By applying the thesaurus, 1202 key terms were identified with a minimum of 4 occurrences, which were analyzed through the DBMS, as below specified. However, in order to improve readability, the co-word map was derived from the key terms with at least 7 occurrences.

By overlaying additional information, such as citation (revealing the scientific impact of specific topic) and average publication year (revealing trends) onto the co-word map, we produced two additional maps. In the citation map, the color of a term is determined by the normalized average citation impact of the publications where the term occurs (average normalized number of citations, ANC). This value can provide more complete information about the interest of the topics represented by the key items. In the average year publication (AYP) map, the color of a term indicates the AYP of all the publications in which the term occurred.

The same VOSviewer data processing described above was applied to the subBDs, and the corresponding co-word, citation and AYP maps were produced.

For both BD and subBDs, quantitative analyses were also performed, through DBMS using the *map* and *network files* provided by VOSviewer, which are text files containing information about the items in the maps, as weight, AYP, ANC and strength of links between items (metrics).

For a comparison among sub-periods, the relative weights of items were computed as the ratio between the key term occurrences and the maximum occurrence count for each sub-period.

3. Results and discussion

3.1. *Most productive journals*

The documents retrieved were published in a total of 1162 sources, but more than 50% contained only one document. The top 20 most productive journals, which account for the 28.3% of the total publications, are reported in Fig. 2. The figure shows the important role played by journals related to hydrology and water management, i.e. Agricultural and Water Management, Water, Irrigation Science, Hydrology and Earth System Sciences, a finding that agrees with other bibliometric studies (Yildirim et al., 2022; Yilmaz and Yilmaz, 2021). In addition, other reference journals for the theme investigated are those dealing with remote sensing, i.e. Remote Sensing, International Journal of Remote Sensing, Remote Sensing of Environment, which is in line with studies that also considered articles published in most recent years (Wang et al., 2022; Yildirim et al., 2022), confirming the increasing role of remote sensing in drought monitoring.

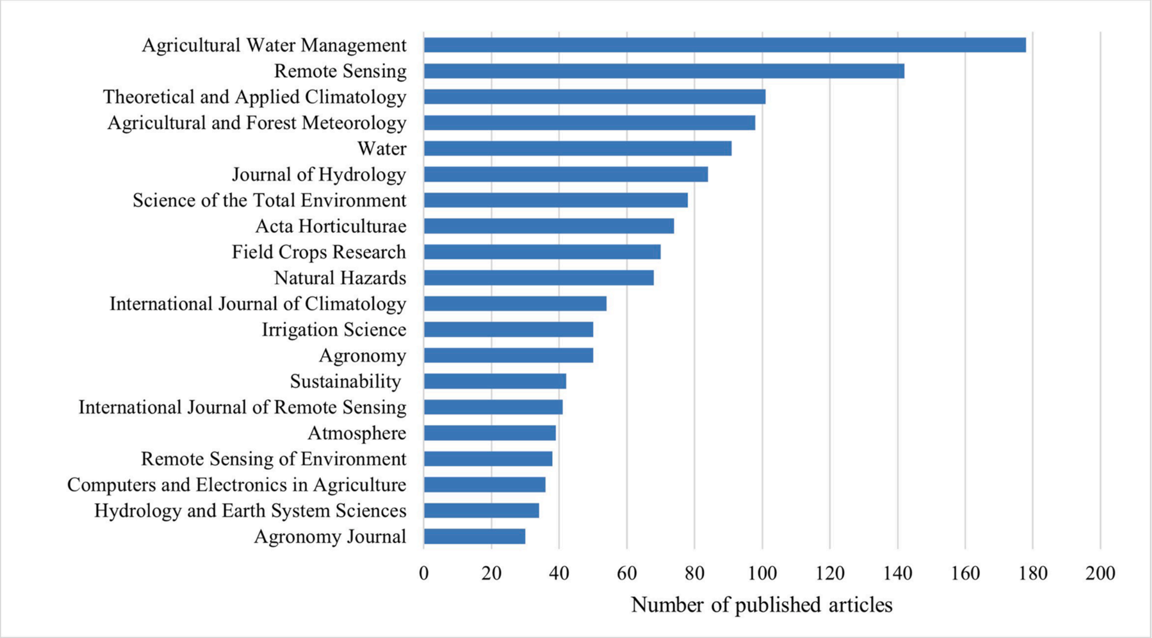

Fig. 2. Number of published articles of the top 20 most productive journals.

3.2. *Co-occurrence analysis and main research themes*

Fig. 3 shows the co-word map obtained for drought and heat indices in agriculture. The map is made up of 886 key terms that occurred at least 7 times in title or abstract. Overall, 5 clusters were detected, whose size ranges from 121 to 223 terms (Table 1). The largest cluster, colored in yellow, on the left side refers to analyses of drought at different time scales, i.e. meteorological, agricultural, and hydrological, mainly at a river basin level. Most representative key terms of this cluster are *precipitation* (1400 occurrences), *drought indices* (936) and *agricultural drought* (556), as well as the main indices for drought monitoring *SPI, SPEI* and *PDSI* (Palmer Drought Severity Index). The red cluster on the lower left side, which includes 197 items, refers to risk analyses of climate change impact, adaptation, and socioeconomic issues and its most representative terms are *impact* (1129), *climate* (852), *temperature* (779), *climate change* (659) and *risk* (350). In the lower positions, indices of extreme climate such as *TN90p* (the percentage of days above the 90th percentile of minimum temperature), *extreme temperature index* and

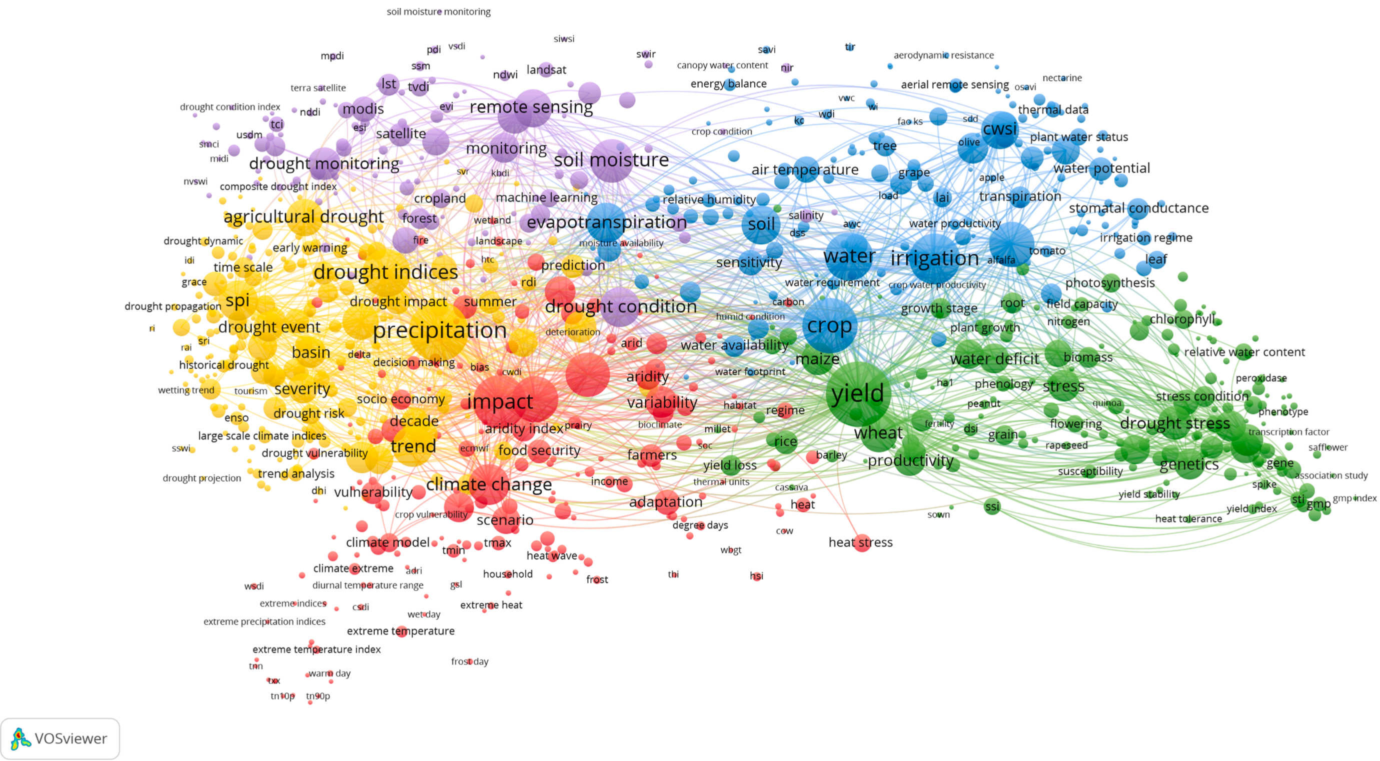

Fig. 3. Co-word map based on drought and heat indices in agriculture for the period 1950–2022. The size and the color of a term indicate, respectively, the number of publications in which the term occurs and the cluster it belongs to. An interactive version of the map is available in the Supplementary materials.

Table 1
The top 25 most frequent key terms for each cluster. The weight corresponds to the number of occurrences.

Analyses of drought at different time scales (Yellow cluster, $n = 223$)		**Risk analyses of climate change**(Red cluster, $n = 197$)		**Drought effects at crop/ plant level** (Green cluster, $n = 186$)		**Water resource management** (Blue cluster, $n = 159$)		**Drought monitoring from remote sensing** (Purple cluster, $n = 121$)	
Label	Weight	Label	Weight	Label	Weight	Label	Weight	Label	Weight
Precipitation	1400	impact	1129	yield	1672	crop	1223	soil moisture	765
drought indices	929	climate	852	wheat	561	irrigation	1016	drought condition	647
Trend	667	temperature	779	drought stress	458	water	916	remote sensing	587
SPI	624	climate change	659	maize	429	water stress	815	NDVI	472
agricultural drought	556	variability	405	drought tolerance	412	evapotranspiration	633	drought monitoring	434
drought intensity	518	management	390	productivity	410	soil	612	monitoring	361
Seasonality	413	risk	350	stress	398	CWSI	578	vegetation	300
Frequency	408	scenario	321	genetics	391	irrigation management	380	spatial analysis	271
Basin	373	aridity	264	trait	388	canopy temperature	322	MODIS	253
Severity	369	adaptation	258	genotype	382	air temperature	275	satellite	220
drought event	364	policy	247	water deficit	365	sensitivity	263	vegetation indices	202
water resource	342	Aridity Index	227	growth	348	canopy	252	LST	191
SPEI	335	ecosystem	221	grain yield	331	water potential	226	forest	180
Duration	313	food security	217	phenological stage	303	water management	222	VCI	158
Intensity	310	vulnerability	202	cultivar	255	water use	213	weather data	154
Decade	292	farmers	201	rice	224	water status	201	topography	146
river basin	266	climate zone	190	tolerance	202	water availability	196	cropland	145
drought period	252	sustainability	175	interaction	189	transpiration	194	capability	140
meteorological drought	244	agricultural management	173	rainfed	188	stomatal conductance	190	TVDI	129
drought impact	241	weather	169	stress condition	184	water stress indices	187	machine learning	129
PDSI	236	socio economy	160	biomass	175	tree	184	agricultural drought monitoring	114
Prediction	231	climate model	149	yield loss	174	water supply	182	moisture	112
drought frequency	215	heat stress	135	Root	173	water scarcity	181	surface temperature	110
Hydrology	211	water balance	119	growth stage	171	water use efficiency	170	land use	105
Summer	210	crop model	113	Grain	156	LAI	148	land cover	100

WSDI (Warm Spell Duration Index), are also included in this cluster.

The green cluster on the lower right side, refers to drought effects at crop/plant level. Terms on the left part of this cluster are related to crops (*wheat* and *maize* are the most represented, with 561 and 429 occurrences respectively) and their *yield* (1672)/*productivity* (410), while the right side is mostly related to plant responses as shown by the main key terms, e.g. *drought stress* (458), *drought tolerance* (412) and *genetics* (391), which is very important for enhancing crop drought tolerance (Roca Paixão et al., 2019; Villalobos-López et al., 2022). The blue cluster, on the upper right side refers to water resource management and consists of items such as *crop* (1223), *irrigation* (1016) and *water stress* (815). The purple cluster on the upper left side is related to the drought monitoring from remote sensing and its relative indices, and the most represented items are *soil moisture* (765), *remote sensing* (587) and *drought monitoring* (434). It should be noted that remote sensing is also cited in the blue cluster, but in this case, it refers to *aerial remote sensing* (80) or *unmanned aerial vehicle* (61), which are more appropriate monitoring tools for water management. Drought monitoring tools have in fact incorporated many remote sensing indices which ensure timely information to police makers (Crocetti et al., 2020).

It is remarkable that in the map, the spatial scale of analysis increases from left to right, going from a regional to a plant level. It is also interesting to highlight the central position of the key term *evapotranspiration*, which plays a role of bridge between water resource management (blue cluster) and drought monitoring from remote sensing (purple cluster). A similar function can be attributed to the terms *water scarcity, water availability, water footprint*, which are also located in the middle of the map.

Wang et al. (2022) published a co-occurrence network of agricultural drought which presents many similarities with our analysis, identifying 3 clusters related to the impact of climate change (like our red cluster), drought monitoring from remote sensing (like our purple cluster) and soil moisture, precipitation and evapotranspiration (comparable to our blue cluster). Ekundayo et al. (2022) also presented a co-word map on drought research including 3 main clusters, one of which could be considered a synthesis of our yellow and red clusters, while the content of our green cluster was split into two sub-clusters, distinguishing crop genetics from physiology and biochemistry.

The bibliometric analysis conducted by Cui et al. (2022) on high temperature and drought stress is only partially comparable to the current study, because it focused on the effects on plants, without considering indices for monitoring heat and drought at larger scale. Their co-word map (only based on keywords) mainly included the key-terms positioned on the right side of the map presented here (our green cluster). Sweileh (2020) realized a co-occurrence map on food security in the context of climate change which included some clusters analogous to those presented here. In particular, the authors found a cluster representing the crop/plant responses to abiotic and biotic stresses where drought plays an important role (similar to our green cluster) and another more related to water management (similar to our

Table 2
The 10 key terms with the strongest links with the Drought terms and the Heat terms.

Drought terms		Heat terms	
Linked key terms	Link_sum	Linked key terms	Link_sum
Yield	3569	temperature	140
Precipitation	3383	impact	122
Impact	2442	yield	121
SPI	2427	trend	101
soil moisture	1699	precipitation	64
Trend	1450	wheat	60
Severity	1310	risk	57
SPEI	1300	scenario	55
drought indices	1286	stress	47
Water	1273	intensity	41

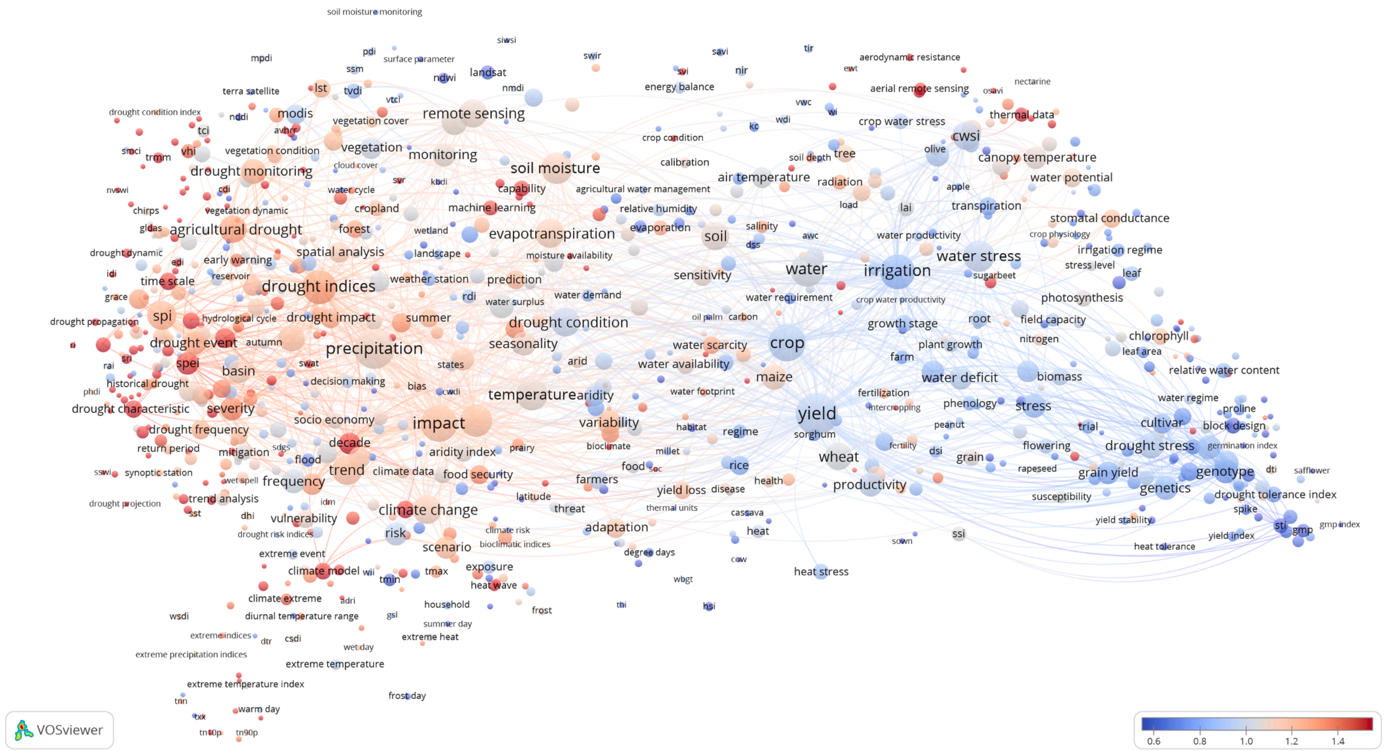

Fig. 4. Co-word citation map on drought and heat indices in agriculture for the period 1950–2022. As the average citation impact of a term varies from minimum to maximum, the resulting color varies from blue to red. An interactive version of the map is available in the Supplementary materials.

blue cluster).

Among all items extracted by VOSviewer, 103 and 5 key terms are referred to drought and heat, respectively (hereinafter referred to as "drought terms" and "heat terms"). Drought terms are included in all clusters and are mostly represented by items such as *drought indices* (929 occurrences), *water stress* (815) and *agricultural drought* (556).

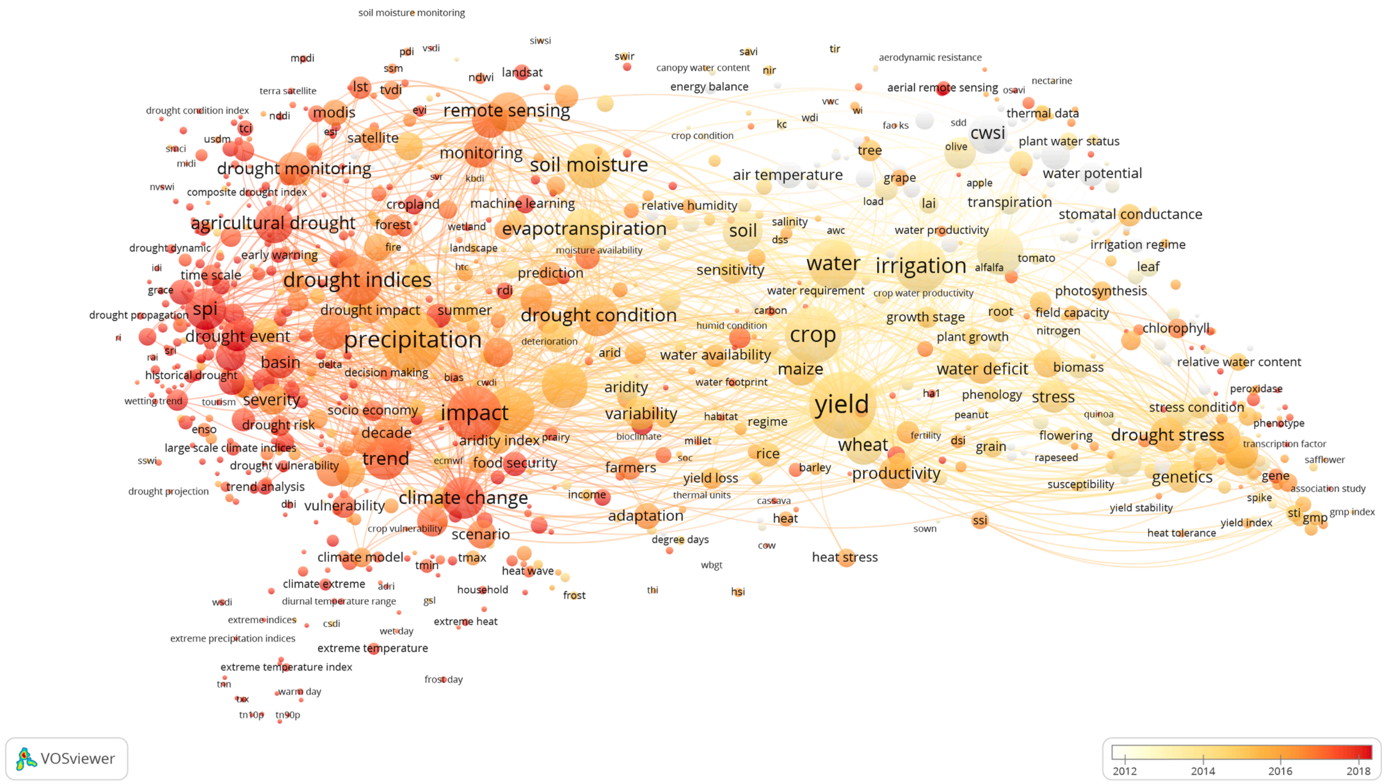

Fig. 5. Average publication year map (AYP) on drought and heat indices in agriculture for the period 1950–2022. The color of a term indicates the average publication year of the publications in which the term occurs (red term are more recent). An interactive version of the map is available in the Supplementary materials.

Conversely, heat terms are only associated to the red cluster (climate risk analyses) and are represented by *heat stress* (135), *extreme temperature* (55) and *heat wave* (49).

Focusing on the links among terms, the 10 terms with the highest number of co-occurrences with drought and heat terms are listed in Table 2. *Yield* and *impact* are at the top for both groups, while other common terms are *precipitation* and *trend.* Moreover, *SPI* and *SPEI* drought indices show very strong link with drought terms, whereas *risk* and *scenario*, which are strictly connected to global warming, show the strongest links with heat terms.

Surprisingly, very low number of links were found between drought and heat terms, at most 39 links between *heat wave* and drought terms. This finding is in contrast with the current scientific interest on plant responses to the combined water-deficit and heat stress (Cui et al., 2022; Sinha et al., 2021). These differences can be explained considering that our literature search strategy was specifically targeted on drought and heat indices. In fact, the queries to retrieve scientific literature did not consider documents without an explicit reference to the terms “indices” or “indicators” in their title, abstract or keywords, thus, some articles could have been left out. Furthermore, some subjectivity was unavoidable in the selection of thesaurus terms and the minimum number of occurrences for mapping. This fact could have led to the loss of some specific topics, despite a general improvement in research mapping.

3.3. Citation and average publication year maps

The co-word citation map is presented in Fig. 4. The map shows that the hot terms (connected to highly cited publications) are mainly located on the left side. Some items such as *drought characteristics, timescale, SPEI, drought indices, agricultural drought* and *SPI* (related to drought monitoring at different time scales), *climate change, climate model, heat wave* and *impact* (related to climate change risk), *machine learning* (a powerful tool also for drought monitoring by remote sensing) have high scores for both citation impact and weight. Some highly rated terms are also present on the upper right side, as *aerial remote sensing* and *thermal data*, which are used for precision irrigation. In the research field on risk analyses of climate change, the much greater citation impact of the term *tmax* (maximum temperature) compared to *tmin* (minimum temperature) is noteworthy.

The average year of publications (AYP) on drought and heat indices in agriculture is displayed in Fig. 5. The AYP provides indications on the qualitative trends of the scientific literature, that is the highest values are associated to the so-called "trending research topics", which are covered by the most recent publications. Colors in this map range from white to red. White terms are those mainly occurring in oldest publications, whereas red terms are those more frequent in recent publications. The average year ranges from 2012 to 2018 approximately. Overall, the map confirms the principal gradient from right to left detected in the co-word citation map, which mirrors the vibrance of research in drought monitoring and drought risk but also a decreasing attention to water management and drought effects on crops/plants. Our analysis highlighted that items related to field/plant scale studies (on the right side of the map) show an older AYP than items related to larger scale analyses (see the key terms *basin, remote sensing,* and many associated words). Consistent with this finding, a tendency to extend the area of analysis has been observed in some studies (Crocetti et al., 2020; Mishra and Singh, 2010).

3.4. Indices retrieved

Unlike previous bibliometric analyses on drought indices, which started from a predefined list of indices (Kchouk et al., 2022; Yildirim et al., 2022), the present study applied a bottom-up approach, based on specific queries which focused on the closeness between drought/heat and the terms “index” or “indicator”. As expected, among the key items, several indices were identified, in relation to drought or heat. The Supplementary TabS2, TabS3a and TabS3b report the complete list of the drought and heat indices retrieved in this study. Overall, drought indices seem to be more standardized and largely adopted than heat indices. Considering those with at least 4 occurrences, a total of 124 drought indices were retrieved, with a weight (in terms of occurrences) reaching 624. As reported in Table 3, the most frequent index is the SPI, followed by the Crop Water Stress Index (CWSI). These 2 top indices show similar weights, but their AYP suggests that the first one prevails in the recent literature. However, CWSI looks to still be the most important index for research on water stress and irrigation (blue cluster). Considering both AYP and weight, SPI, SPEI and Vegetation Condition Index (VCI) attract the greatest interest. SPI and SPEI are widely applied for large scale analyses of drought (yellow cluster) together with PDSI which seems to be less applied in more recent studies. The main indices for drought monitoring from remote sensing (purple cluster) are NDVI (Normalized Difference Vegetation Index), VCI and TVDI (Temperature Vegetation Dryness Index). The Aridity Index (AI) shows the highest weight for risk analyses of the climate impact (red cluster), while Stress Susceptibility (SSI) and Stress Tolerance (STI) indices are the most represented for studies at crop/plant level (green cluster).

We retrieved a total of 20 heat indices, the top 10 of which are reported in Table 4. The highest weight is shown by the Temperature Condition Index (TCI), which has the particularity to be also used for analyses on drought; indeed, it is linked to studies on remote sensing applied to drought monitoring (purple cluster). The majority of other indices (in the table marked with an asterisk) derive from the Expert Team on Climate Change Detection and Indices (ETCCDI) (Klein Tank et al., 2009) and are linked to water stress and irrigation studies (green cluster). Compared to drought indices, their weight is relatively low, reaching 16 occurrences for Warm Spell Duration Index (WSDI), but their AYP show that they are mainly applied in the most recent literature. In 4th position, with 14 occurrences, the Stress Degree Days (SDD) represents studies at crop/plant level (green cluster), although its

Table 3
The top 10 drought indices based on their weight (number of occurrences).

Name	Acronym	Cluster	Weight	AYP
Standardised Precipitation Index	SPI	yellow	624	2018
Crop Water Stress Index	CWSI	blue	578	2012
Normalized Difference Vegetation Index	NDVI	purple	472	2017
Standardised Precipitation Evapotranspiration Index	SPEI	yellow	335	2019
Palmer Drought Severity Index	PDSI	yellow	236	2015
Aridity Index	AI	red	227	2016
Vegetation Condition Index	VCI	purple	158	2018
Temperature Vegetation Dryness Index	TVDI	purple	129	2017
Stress Susceptibility Index	SSI	green	127	2016
Stress Tolerance Index	STI	green	113	2015

Table 4
The top 10 heat indices based on their weight (number of occurrences).

Name	Acronym	Cluster	Weight	AYP
Temperature Condition Index	TCI	purple	94	2018
Heat Stress Index/indices	HSI	red	35	2016
Warm Spell Duration Index	WSDI*	blue	16	2020
Stress Degree Days	SDD	green	14	1999
Monthly maximum value of daily maximum temperature	TXx*	blue	13	2019
Percentage of days when TN > 90th percentile	TN90p*	blue	10	2020
Percentage of days when TX > 90th percentile	TX90p*	blue	10	2020
Monthly maximum value of daily minimum temperature	TNx*	blue	9	2021
Heat Susceptibility Index	HS or HSI	red	7	2015
Tropical Night	TR*	blue	7	2020

* ETCCDI indices.

Table 5
The 45 indices with a highest Average Normalized Citation score (ANC), grouped by cluster.

Cluster	Fields of application	Acronym	Name	ANC	Weight	AYP
yellow	Soil moisture	SSWI	Standardized Soil Water Index	2.78	7	2015
yellow	Soil moisture	SSMI	Standardized Soil Moisture index	2.51	32	2020
yellow	Hydrology	RI	Runoff Index	2.49	11	2018
yellow	Soil moisture	SMDI	Soil Moisture Deficit Index	2.33	12	2019
yellow	Hydrology	IDI	Integrated Drought Index	2.33	15	2019
yellow	Meteorology	SEDI	Standardized Evapotranspiration Deficit Index	2.20	9	2019
yellow	Soil moisture	ETDI	Evapotranspiration Deficit Index	2.16	7	2017
yellow	Meteorology/ Remote sensing	MSDI	Multivariate Standardized Drought Index	2.14	19	2019
yellow	Meteorology	MPDSI	Modified Palmer Drought Severity Index	1.86	7	2018
yellow	Hydrology	SRI	Standardized Runoff Index	1.83	41	2018
yellow	Meteorology	ZSI	Palmer Z Index	1.75	28	2015
yellow	Meteorology	sc-PDSI	Self-calibrating Palmer drought severity index	1.75	15	2017
yellow	Soil moisture	TWS	Total Water Storage	1.67	9	2019
yellow	Meteorology	EDI	Effective Drought Index	1.53	27	2017
yellow	Hydrology	SSFI	Standardized Streamflow Index	1.48	12	2019
yellow	Meteorology	SPEI	Standardized Precipitation Evapotranspiration Index	1.47	335	2019
yellow	Meteorology	PDSI	Palmer Drought Severity Index	1.47	236	2015
yellow	Meteorology	eRDI	Effective Reconnaissance Drought Index	1.39	7	2020
yellow	Meteorology	SPI	Standardized Precipitation Index	1.23	624	2018
red	Climate extremes	CDD	Consecutive Dry Days	1.67	13	2020
red	Climate extremes	TX90p	Percentage of days when TX > 90th percentile	1.37	10	2020
red	Climate extremes	WSDI	Warm Spell Duration Index	1.16	16	2020
green	Physiology	DFI	Drought Factor Index	1.41	8	2012
green	Physiology	DRI	Drought Response Index	1.26	22	2010
blue	Remote sensing	OSAVI	Optimized Soil Adjusted Vegetation Index	2.61	12	2018
blue	Remote sensing	PRI	Photochemical Reflectance Index	2.33	30	2016
blue	Remote sensing	RDVI	Renormalized Difference Vegetation Index	2.07	10	2017
purple	Remote sensing	MIDI	Microwave Integrated Drought Index	2.65	8	2018
purple	Meteorology	CWB	Climatic Water Balance	2.60	13	2015
purple	Remote sensing	SDCI	Scaled Drought Condition Index	2.17	10	2019
purple	Meteorology	AWD	Atmospheric water deficit	2.05	14	2018
purple	Remote sensing	SMCI	Soil moisture condition index	1.87	17	2020
purple	Remote sensing	ESI	Evaporative Stress Index	1.86	21	2018
purple	Soil moisture	SMA	Soil Moisture Anomaly	1.84	18	2018
purple	Soil moisture	SWDI	Soil Water Deficit Index	1.68	37	2018
purple	Remote sensing	SMADI	Soil Moisture Agricultural Drought Index	1.63	10	2019
purple	Remote sensing	NVSWI	Normalized Vegetation Supply Water Index	1.61	11	2020
purple	Hydrology/ Remote sensing	CDI	Composite Drought Index	1.61	25	2020
purple	Remote sensing	VegDRI	Vegetation Drought Response Index	1.50	12	2017
purple	Remote sensing	PCI	Precipitation Condition Index	1.47	21	2020
purple	Remote sensing	EVI	Enhanced Vegetation Index	1.43	54	2018
purple	Remote sensing	VHI	Vegetation Health Index	1.41	100	2019
purple	Meteorology/ Remote sensing	CDI	Combined Drought Indicator	1.40	29	2020
purple	Meteorology	CMI	Crop Moisture Index	1.16	24	2008

application seems less frequent in the last years (AYP=1999). The research on risk analyses of the climate impact (red cluster) is represented by the Heat Stress indices.

It should be noted that the retrieved “heat stress” index/indices correspond to several different formulations. Four types of indices can be distinguished based on: a) heat accumulation above a critical air temperature or between a lower and an upper threshold (Teixeira et al., 2013); b) heat accumulation above a critical soil temperature; c) number of days (consecutive or not) when temperature overcomes a threshold (He et al., 2018); d) differences between canopy temperature and ambient air temperature immediately above the canopy (Ibrahim, 2011) (see also Supplementary TabS3b).

The citation analysis showed that several indices with a low number of occurrences have greater research impact than others (Table 5). The indices with a highest citation score are quite exclusively related to drought, except for the two heat indices TX90p (percentage of days when maximum temperature > 90th percentile) and WSDI.

The highest impact was found for the Standardized Soil Water Index (SSWI), which is a drought index associated to hydrological topics in the yellow cluster. This result mainly derives from studies related to climate scenarios (Duan and Mei, 2014; Leng et al., 2015; Wang et al., 2011) and spatial drought patterns (Vidal et al., 2010). The majority of “hot" indices are included in purple and green clusters (Table 5). The Microwave Integrated Drought Index (MIDI), belonging to the purple cluster, is a remotely sensed index applied for meteorological drought monitoring (Zhang and Jia, 2013; Zhang et al., 2017b), whereas the Optimized Soil-Adjusted Vegetation Index (OSAVI), included in the green cluster is reported in highly cited vegetation monitoring studies (Berni et al., 2009).

It is remarkable that despite some indices like CDD, TX90p and WSDI were proposed at the end of the last century (Karl et al., 1999), they all have an AYP equal to 2020, (Fathian et al., 2020; Guan et al., 2022; Shrestha et al., 2017), thus confirming their recent application in risk analysis. On the contrary, indices such as DFI and DRI in the green cluster, show a much lower AYP (2010 and 2012), which confirms that in the last decade studies are mainly focusing on larger scales than the crop/plant level. The 7 indices concerning soil moisture, are all characterized by very high citation scores and recent AYP values (since 2015). Besides the above cited SSWI, the Standardized Soil Moisture index (SSMI) (Afshar et al., 2022), the Soil Moisture Deficit Index (SMDI) and the Evapotranspiration Deficit Index (ETDI) (Narasimhan and Srinivasan, 2005) have an ANC value above 2.

A special type of drought indices derives from the combination of different variables, data types (meteorological, hydrological, remote

Table 6
The top 25 crops based on their weight (number of occurrences).

Crop	Cluster	Weight	AYP
wheat	green	561	2014
maize	green	429	2015
rice	green	224	2015
soybean	green	121	2014
grape	blue	112	2016
cotton	blue	111	2008
legume	green	80	2013
barley	green	72	2015
sorghum	green	71	2012
potato	green	62	2014
cereal	green	58	2015
tomato	blue	58	2013
sugarcane	blue	57	2014
olive	blue	43	2016
peanut	green	36	2012
sunflower	blue	36	2011
peach	blue	30	2013
rapeseed	green	30	2012
common bean	green	29	2015
chickpea	green	28	2010
alfalfa	blue	25	2010
fruit tree	blue	25	2012
sugarbeet	blue	25	2011
apple	blue	24	2014
millet	green	23	2017

sensed, model outputs), or different indices. Examples of these indices are the composite drought index and the combined drought indicator in the purple cluster and the integrated drought index in the yellow cluster, with an AYP between 2019 and 2020. However, the use of these terms denotes some ambiguities, as they are applied with different meanings. For instance, the same name Integrated Drought Index (IDI) is assigned to an index that combines i) meteorological, hydrological, and agricultural factors (Huang et al., 2015), ii) SPI and VHI indices (Brito et al., 2018) or iii) the response of meteorological, hydrological and agricultural droughts (Shah and Mishra, 2020). The term Combined Drought Indicator (CDI) is used with less ambiguities and refers to a specific index defined by the WMO (WMO and GWP, 2016) which is based on SPI, model-derived Soil Moisture Anomaly (SMA) and fraction of Absorbed Photosynthetically Active Radiation (fAPAR) satellite data and shows a quite high citation impact (Sepulcre-Canto et al., 2012). Revised versions of this indicator use different soil moisture and satellite-based vegetation indices (Bayissa et al., 2019; Kulkarni et al., 2020). An improved version of CDI has been recently proposed by Cammalleri et al. (2021) for the European Drought Observatory (EDO). The most cited example of Composite Drought Index (CDI) is a multivariate index that considers variables related to different drought types (Waseem et al., 2015). We also found at least one case of Composite Drought Index (CDI) which corresponds to a revised Combined Drought Indicator (Fragaszy et al., 2020). However, there is an increasing interest to develop this kind of indices as highlighted by the very recent multivariate drought index SPESMI (Standard Precipitation, potential Evapotranspiration, and root-zone Soil Moisture Index) (Xu et al., 2021), which is being receiving a considerable attention from the scientific community.

It should be noted that in our analysis we found the SPESMI index as well as other compound indices related to drought and heat that were reported in studies published after 2020 (Muthuvel and Mahesha, 2021; Wu et al., 2022; Wu et al., 2020; Yu and Zhai, 2020). Nevertheless, as these terms did not overcome the minimum number of 4 occurrences (that was our occurrences' threshold) they were not included in the analysis.

The remarkable difference between the availability of drought and heat stress indices can also be explained by their different physiological background. Crop responses to drought are in fact much easier to estimate than crop responses to critical temperatures, which mainly depend on crops and varieties, and require more specific calibration. Consequently, while for drought several indices of global validity have been developed, heat stress is better described by crop-specific indices (Teixeira et al., 2013). Moreover, leaf temperatures depend on drought conditions (Perera et al., 2019) making the separation of effects quite difficult as drought and heat are often occurring in combination (Lobell et al., 2013).

3.5. *Main crops studied*

A particular focus of our study concerns the link between drought and heat indices and crops. Overall, 68 key terms referring to crops have at least 4 occurrences, including some general terms (*cereal, forage, legume, fruit tree*). Among the top 25 crops (based on their weight), *wheat* is the most investigated, reaching 561 occurrences (Table 6). Crop terms are associated to the green cluster (14 items), and to the blue cluster (11 items). AYP values show the recent interest in *millet, olive* and *grape*. For genetics studies aimed to improve drought tolerance, the most investigated crops are *cereals*, as *rice, wheat* and *maize* (Villalobos-López et al., 2022). Despite *quinoa* is not included in Table 6, due to its low weight (only 7 co-occurrences), this crop reached the highest ANC score (1.51) and it has emerged as a quite recent hotspot in the scientific literature

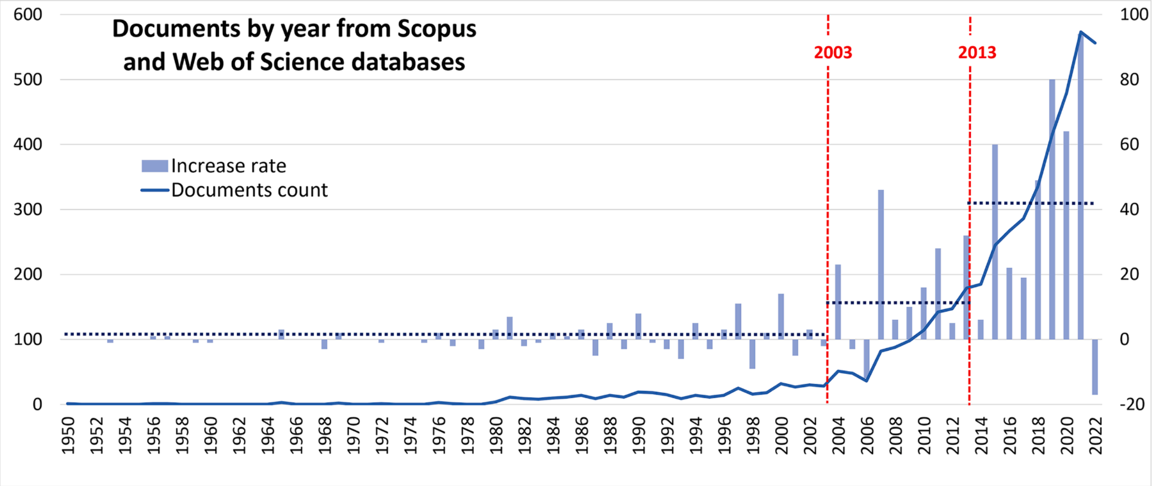

Fig. 6. Trends of scientific publications about drought or heat events in agriculture. The red dotted lines identify the two break points in the time series and the blue dotted lines correspond to the average number of the increase rate for the 3 subBDs.

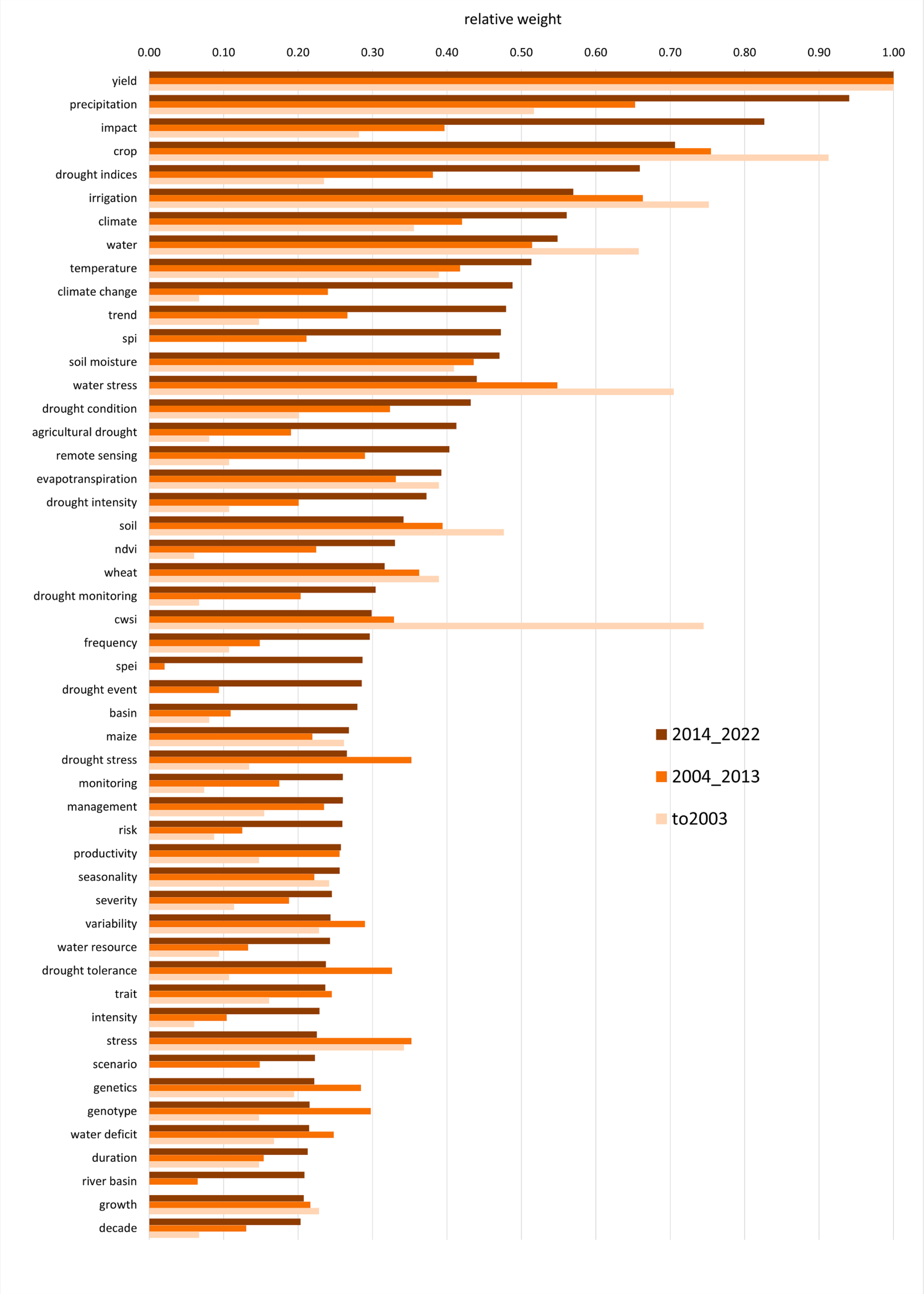

Fig. 7. Relative weights of the main key terms in the three periods analyzed.

(AYP=2019) (Saddiq et al., 2021). Such interest is linked to the quinoa stress tolerance, particularly in relation to water scarcity and salinity (Ruiz et al., 2014). It is remarkable that for some of the most frequent crops retrieved by our analysis, mainly cereals and legumes, the combined effects derived from drought and heat were investigated in several studies (Cohen et al., 2021a, 2021b; Jagadish et al., 2011; Lawas et al., 2018; Mahrookashani et al., 2017; Mittler, 2006).

3.6. *Trends of scientific production during the period 1951–2022*

Since the end of the last century the scientific production for drought and heat in agriculture has been growing at an exponential rate. This finding is in line with other bibliometric studies on drought and/or heat research (Cui et al., 2022; Ekundayo et al., 2022; Wang et al., 2022; Yilmaz and Yilmaz, 2021). The Fig. 6 reports the distribution by year of the retrieved 4948 publications and their annual increment. Applying the Standard Normal Homogeneity Test (SNHT) to identify the presence of break points in the series of the annual publication rate, two significant slope changes were detected, at 2003 ($p<0.001$) and 2013 ($p<0.05$) years. Since 2007, the curve rises constantly until 2022.

In the light of these observations, the database (BD) was divided in three subBDs, related to the sub-periods 1950–2003, 2004–2013 and 2014–2022, and the most representative key terms were identified with VOSviewer for each subBD. Sub-period co-word maps (Supplementary FigS1, FigS2 and FigS3) were then generated which allowed to identify the evolution of research fields, showing that themes related to risk analysis of climate change (red cluster) and drought monitoring from remote sensing (purple cluster) emerged only in the last sub-period (2014–2022). The Fig. 7 allows for a comparison among subBDs based on the relative weights of the main items (ratio between the key term occurrences and the maximum occurrences value for each subBD). Then, all items of the most recent period which have a relative weight of at least 0.2 were compared with the same items in the other two subBDs. The relative weight of *precipitation* shows an increase from 0.52 to 0.94, likely due to its growing scarcity (as highlighted by the trend of many items related to drought monitoring) and regime irregularity. *Temperature* relative weight rose from 0.39 to 0.51 and a very remarkable increase in weight was also observed for terms like *impact, climate change, scenario* and *trend*. Altogether, these findings mirror the growing interest in global warming. Our analysis also showed a rising interest in large scale studies, as confirmed by the growing relative weights of *remote sensing, basin* and *river basin*, on the one hand and *SPI, NDVI* and *SPEI* on the other. Conversely, an opposite behavior is observed for *CWSI*.

Items related to plant-scale studies, like *drought stress, drought tolerance, genetics, genotype* and *trait*, have reduced their relative weight in the most recent years after a previous period of prevalent interest. These results are in line with other studies that found decreased interest in drought stress (Cui et al., 2022). Moreover, the relative weight of some terms related to agricultural management (*irrigation, water stress, crops, soil*) has also decreased, even if their absolute frequency increased 5–6 times from the 1st to the 3rd sub-period. Field trials are very demanding, in terms of time, effort and costs, and are therefore less attractive than global studies. These aspects can justify their lower growth rate of local- compared to global- studies. On the other hand, at small scale, suitable remote sensing data is more expensive and less available and requires more processing effort than at larger scales.

4. Conclusions

Under the ongoing global warming, drought and heat extreme events are increasing in frequency and intensity. While adversely affecting the environment, these changes will have inevitable socioeconomic consequences. By combining bibliometric science mapping and break-point analyses to synthetize the global research published on drought and heat indices applied in agriculture in the 1950–2022 period, this study provides a first comprehensive view of the research theme. Such information could be valuable for researchers as well as for policy makers.

Thanks to a bottom-up approach, we retrieved 124 drought indices and 20 heat indices in the literature, with the former being more standardized and largely adopted than heat indices. The largest occurrences were found for SPI and CWSI, both drought-related, but their research impact is currently overcome by other indices such as SSWI, MIDI and OSAVI, mainly based on remote sensing data.

Five major research fields have been identified connected to these indices, namely, analysis of drought at different time scales, risk analysis of climate change, drought effects at crop/plant level, water resource management, and drought monitoring from remote sensing. Among crops, quinoa has emerged as a quite recent hotspot particularly in relation to water scarcity and salinity. Research frontiers, as identified by the bibliometric analyses, mainly belong to research fields concerning drought analysis at different scales, drought monitoring from remote sensing and climate change risk, in particular related to maximum extreme temperatures. The change of focus from crop/field to large scale is due to the need to address climate change challenges from a global perspective. It should be noted that limitations in resource availability could also affect studies at small scale, which require long-term experiments and more expensive equipment. The growing availability of open global spatial datasets, including remote sensing, together with powerful analysis tools, i.e. machine learning, aerial remote sensing and thermal data (for precision irrigation), helps the development of new indices for wide area analyses which are gaining a relevant research impact.

On the other hand, the need to describe complex phenomena requires an increasing complexity of functions applied, as confirmed by the rising number of indices derived from the combination of different variables, data types or indicators. Among them, it is noteworthy to mention compound indices targeted to describe events of simultaneous drought and heat extremes. For this latter category, it seems that no well-established indices have yet emerged.

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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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.agrformet.2023.109626 and is also available from the Mendeley data repository at doi:10.17632/k5gy8nht6j.1.

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