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Integrating Climate Change Education: Opportunities, Challenges, And Innovative Approaches

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ABSTRACT. Climate change is a global challenge that requires collective action, including through education. This study aims to explore the opportunities, challenges, principles, and approaches in climate change education through a systematic analysis of 10 scientific articles published in the last five years in Scopus-indexed journals. The findings indicate that the main opportunities for climate change education include student engagement as agents of change, the strategic role of teachers, supportive learning environments, curriculum integration, science education, and supportive government policies. However, significant challenges remain, such as improving teacher competency, material complexity, limited curriculum tools, collaboration between stakeholders, and gaps between student knowledge and skills. In addition, six main principles of climate change education implementation were found, including improving teacher competency, curriculum adjustment, cross-sector collaboration, student environmental awareness, providing knowledge related to climate change, and connecting learning with contextual issues. Student-based learning approaches, such as inquiry-based learning, problem-based learning, and project-based learning, have proven effective in delivering complex and contextual materials. This study provides contextual and applicable recommendations for education stakeholders in Indonesia, taking into account the unique social, cultural, and educational policy characteristics of Indonesia.

Keywords: Climate Change Education, Opportunities, Challenges, Learning Approaches, Systematic Literature Review

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1. INTRODUCTION

Since ancient times, climate has been an important part of a civilization, humans and other living things must adapt to their living environment including climate. Climate change occurs globally but its impacts can be felt locally. Indications of climate change include changes in the pattern and intensity of various climate parameters such as air temperature, rainfall, wind, humidity, cloud cover and evaporation [1].

Climate change is the change in the pattern and intensity of climate elements in a certain period of time, usually on average 30 years [2]. Climate change can occur naturally, for example volcanic eruptions, El Nino and La Nina events, continental plate shifts, and solar activity. Climate change is also largely caused by human activities, especially the burning of traditional fuels, which results in the accumulation of greenhouse gases [3] such as increasing urbanization, deforestation, illegal peatland clearing, coastal reclamation, industrialization, and improper waste management [4].

Currently, climate change that is hitting the earth is increasingly worrying, increasing temperatures over time change weather patterns and disrupt the balance of nature. This poses many risks to humans and all other living things on Earth, hotter temperatures, more severe storms, increased droughts, increased ocean volume and temperature, species extinction, food shortages, increased health risks, and poverty [5].

Climate change is a shared responsibility of all human beings on planet earth. Education plays an important role in climate change, first building awareness in mitigation and prevention, second building adaptability, third encouraging a sustainable learning process [6]. Climate change education is education that aims to address and develop effective responses to climate change that helps students

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understand the causes and consequences of climate change, prepares them to live with the impacts of climate change, and empowers them to take appropriate action to adopt a more sustainable lifestyle [7].

Climate change education has undergone significant changes over the past few decades. Many countries have expanded their curricula to include climate change and related topics such as sustainability, renewable energy, and environmental policy [8]. The Indonesian government itself in late August 2024 through the Education Standards, Curriculum, and Assessment Agency, Ministry of Education, Culture, Research, and Technology released the Climate Change Education Guide. The guide, which is intended for regional policy makers, school principals, and teachers, aims to provide an in-depth understanding of the issue of climate change, including its definition and impact on people's lives [9].

The Climate Change Education Guide is the first concrete result of a long planning process for the integration of climate change education into formal education in Indonesia that began in mid-2023 [10]. A little late compared to other countries, this guide also requires development related to content, implementation mechanisms, and outreach strategies so that it can be implemented optimally and effectively. A study of climate change education in Indonesia, namely in geography subjects at the senior high school level, shows that there are opportunities for students' climate change learning in the Basic Competencies in the geography curriculum [11]. However, the syllabus is not supported by materials/topics and learning activities that explicitly address climate change education.

This Systematic Literature Review aims to explore climate change education in various countries to obtain an overview of its implementation in schools so that it can be used as inspiration and adapted in Indonesia. This study will try to find answers from selected literature to the following questions, (1) What are the opportunities and challenges in implementing climate change education? (2) What are the principles in climate change education? (3) What is the right approach to use for climate change education in the classroom?

2. MATERIALS AND METHODS

2.1 Methodology

This study is a Systematic Literature Review (SLR) using the PRISMA (Reporting Items for Systematic Review and Meta-Analyses) method [12]. The process of making an SLR using the PRISMA approach consists of the steps of identification, screening, eligibility, study quality assessment, data extraction and analysis.

2.2 The Review Method

Identificiation

Identification is the initial step by using various appropriate keywords in the process of searching for article sources as references. Based on the formulation of the research problem that has been previously determined, the author uses two main keywords, namely "Climate Change Education" and "Climate Change in School". This search process is carried out in three databases, namely ERIC, DOAJ, and Science Direct. In the three databases, a filter is set against the year of publication, namely the last five years (2020 to 2024). From the identification stage, 584 articles were obtained which will then go through the screening stage. 12 duplicate articles were obtained so that the remaining number is 572 articles. The identification results can be seen in table 1 of the following search series.

Table 1 Search Chain

Keywords	ERIC	DOAJ	Science Direct
Climate change education	24	83	99
Climate change in school	320	12	46
Number of searches	344	95	145

Screening

The screening stage uses inclusion and exclusion criteria consisting of several criteria shown in table 2.

Table 2 Inclusion and Exclusion Criteria

	Inclusion Criteria		Exclusion Criteria
1.	Year of publication from 2020 to 2024	1.	Year of publication before 2020
2.	International articles in English	2.	Article not in English
3.	Educational research	3.	Not educational research
4.	Articles published in journals	4.	Articles in the form of proceedings, Book Chapters, etc
5.	Published in international journals indexed by Scopus	5.	Published not in international journals indexed by Scopus

Inclusion criteria number 1 (year of publication) was applied directly when searching for articles in the database used (at the identification stage). So that 572 articles that entered the screening stage were articles that had passed the first inclusion criteria. At the screening stage, many articles were excluded because five inclusion criteria were applied as in table 2. The number of articles that were removed at the screening stage was 443, leaving 129 articles that would enter the next stage, namely eligibility.

Eligibility

All articles from the screening process will go through a second screening process, namely the eligibility process. This process is carried out to ensure that all selected articles are accurate and suitable for use. This process is carried out by referring to the article title and abstract to find the determining factors that can answer the research questions that have been set. If the determining factors cannot be found, then the next step will refer to the methodology, findings, and discussion sections of the article. From this process, 119 articles were removed and 10 articles remained to be included in the next process, namely quality assessment. The series of article selection processes from the beginning to the end can be seen in figure 1 Flow chart of the research article selection process.

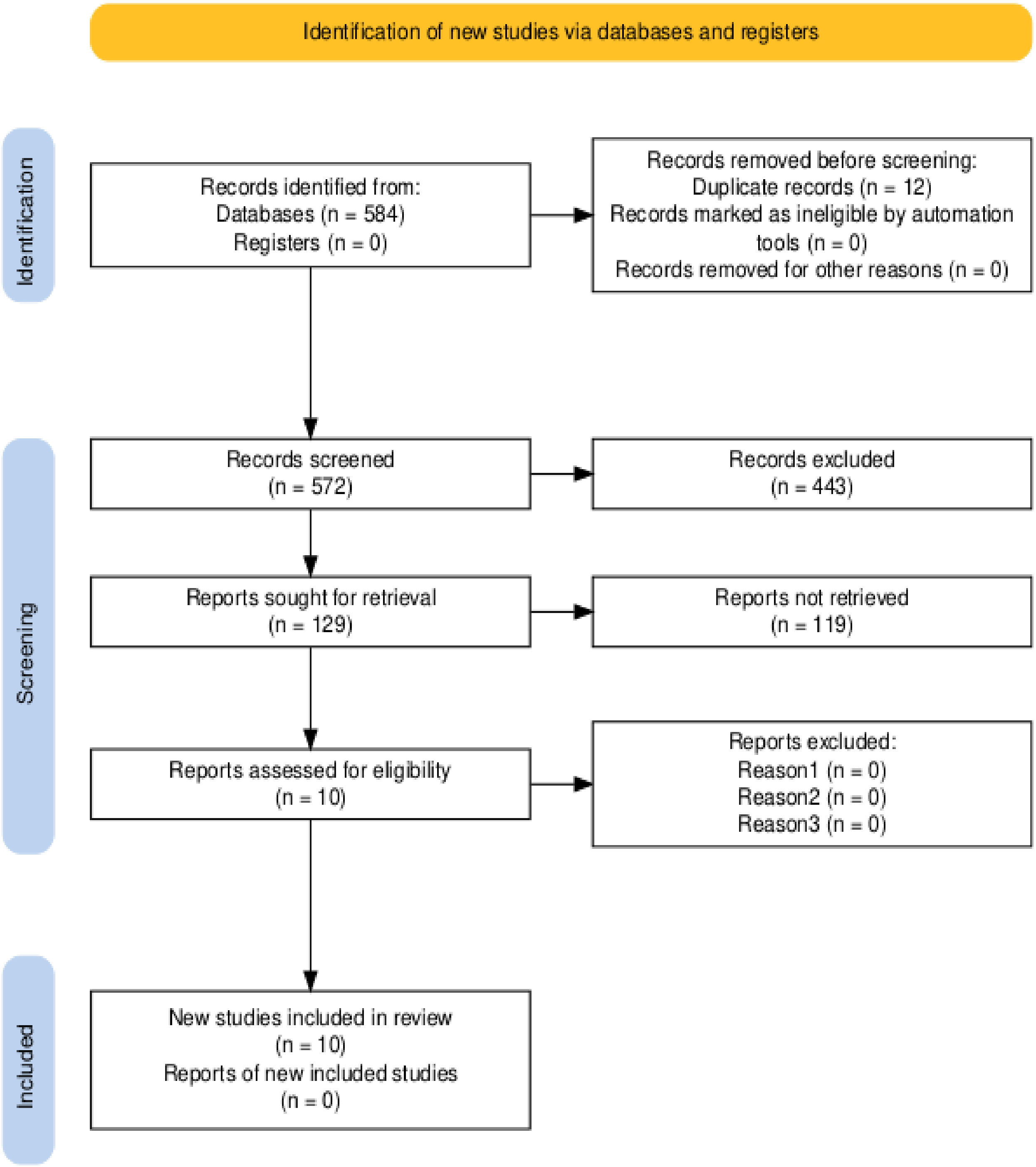

Fig. 1 Flow chart of the research article selection process

Selected articles that passed all stages of the PRISMA method can be seen in table 3.

Table 3 Selected Articles

Title	Year/Author	Methodology	Findings
1 A Climate Change and Sustainability Education Movement: Networks, Open Schooling, and the 'CARE- KNOW-DO' Framework	2023 Alexandra Okada, and Peter Gray	Method : Delphi Subject : 27 Experts Instrument : Questionnaire	1. Climate Change Education needs to be integrated at all levels of education, from formal to informal education 2. The CARE-KNOW-DO framework provides a basis for guiding students in understanding and addressing environmental issues 3. Cross-disciplinary Learning enhances a holistic understanding of climate change
2 Climate change education implementation : the voices of policymakers, professional development providers, and teachers in five countries	2024 Orit Ben Zvi Assaraf, Vaille Dawson, Efrat Eilam, Tuba Gokpinar, Daphne Goldman, Nofar Naugauker, Gusti Agung Paramitha Eka Putri, Agung Wijaya Subiantoro, Sakari Tolppanen, Peta White, Helen Widdop Quinton & Justin Dillon	Method : Qualitative Subjects : 36 participants from 5 countries Instrument : Interview	1. Climate change education needs to be more explicitly integrated into school curricula with approaches that support active learning. 2. While there is support for incorporating CCE, there are still significant challenges to be overcome to ensure effective implementation.
3 Inquiry-Based Learning on Climate Change in Upper Secondary Education: A Design-Based Approach	2022 Sebastian Brumann, Ulrike Ohl and Johannes Schulz	Method : Design Based Research Subjects : 34 teachers and 433 students Instruments : Modules, Observation Sheets	Inquiry Based Learning is a promising approach to climate change education especially in strengthening climate literacy and scientific skills.
4 "Stickier" learning through gameplay: An e□ective approach to climate change education	2021 S. Pfirman, T. O'Garra, E. Bachrach Simon, J. Brunacini, D. Reckien, J. J. Lee & E. Lukasiewicz	Method : experimental Subjects : 41 adults from Greater Boston Instruments : questionnaire, illustrated article, EcoChains: Arctic Crisis cards	1. The EcoChains game was as effective as the article in increasing short-term knowledge about climate change, but more effective in long-term knowledge retention 2. Participants who played the game also reported higher levels of engagement, greater enjoyment, and were more likely to recommend the game to others compared to those who read the article.
5 Using inquiry-based dialogues to explore controversialclimate change issues with secondary students: Anexample from Norway	2022 Lisa Steffensen , Marit Johnsen-Høines and Kjellrun Hiis Hauge	Method : Qualitative Subjects : 4 classes of Norwegian secondary school students Instruments : Audio-video recordings	Inquiry-based dialogue strengthens student engagement in democratic issues and supports real-world issue-based learning.

Title	Year/Author	Methodology	Findings
6 Climate Change Education Challenges from Two Different Perspectives of Change Agents: Perceptions of School Students and Pre-Service Teachers	2022 Veronika Winter, Johanna Kranz, and Andrea Möller	Method : Qualitative Subjects : 80 grade 12 students and 18 pre-service teachers in Austria Instruments : Questionnaire and document analysis	1. Both students and Prospective Teachers feel inadequately prepared to act as agents of change regarding climate change 2. The topic of Climate Change does not receive sufficient attention in the curriculum 3. There are systemic challenges that educational institutions must face to support teacher professional development in the field of CCE.
7 Science Education for Sustainability: Strengthening Children's Science Engagement through Climate Change Learning and Action	2020 Carlie D. Trott, and Andrea E. Weinberg	Methods : mixed-methods Subjects : 55 children aged 10-12 years from the Mountain West, USA Instrument : questionnaire	The program successfully broadened children's understanding of science and strengthened their engagement with sustainability themes. Children became more confident, actively engaged in science classes, and were able to connect science to real-world action.
8 Teaching Atmospheric Hazards in the Climate Change Context—Environmental Didactic Proposals in the Mediterranean Region for Secondary Schools	2021 Álvaro-Francisco Morote, Jorge Olcina, and María Hernández	Method : curriculum analysis Subjects : students at Secondary Education (ages 12-16 years) and Baccalaureate (ages 17-18 years) in Spain Instruments : Qualitative analysis	1. Data-based approaches such as graphical analysis of rainfall and drought trends have been shown to improve student understanding 2. Project-based materials, including fieldwork and climate modeling, help students understand the relationship between natural phenomena and human activities
9 Identifying gaps in climate change education - a casestudy in Austrian schools	2023 Eva Feldbacher, Manuela Waberera, Lena Campostrinib and GabrieleWeigelhofer	Method : case study Subjects : 113 secondary school students (aged 13–17 years) in Austria Instrument : online survey	Climate education needs to be overhauled to improve students' understanding of the complex human-climate relationships. An interdisciplinary approach is needed to help students understand dynamic system interactions and encourage pro-environmental action.
10 'Don't Say It's Going to Be Okay': How International Educators Embrace Transformative Education to Support Their Students Navigating Our Global Climate Emergency	2021 Jeremy Jimenez and Laura Moorhead	Method : qualitative Subject : seven educators and staff Instrument : semi-structured interview	This research suggests that sustainability education should be approached with a transformational approach, where students are encouraged to think independently and develop actions based on their own understanding. Educators strive to create learning environments that support long-term advocacy for environmental and social justice issues.

Study Quality Assessment

The selected articles in the eligibility process amounting to 10 articles need to be evaluated for quality to ensure that only relevant, valid, and high-quality articles are used in further analysis. Before the assessment is carried out, an assessment rubric is first prepared as a reference in assessing the quality of the article as can be seen in table 4.

Table 4 Study Quality Assessment [13]

No	Item	Answer
1	Was the article refereed?	Yes/No
2	Were the aim(s) of the study clearly stated?	Yes/No/Partially
3	Were the study participants or observational units adequately described? For example, students' programming experience, year of study etc	Yes/No/Partially
4	Were the data collections carried out very well? For example, discussion of procedures used for collection, and how the study setting may have influenced the data collected?	Yes/No/Partially
5	Were potential confounders adequately controlled for in the analysis?	Yes/No/Partially
6	Were the approach to and formulation of the analysis well conveyed? For example, description of the form of the original data, rationale for choice of method/tool/package?	Yes/No/Partially
7	Were the findings credible? For example, the study was methodologically explained so that we can trust the findings; findings/conclusions are resonant with other knowledge and experience?	Yes/No/Partially

The article quality assessment answers are converted into a score of 0 for no, 0.5 for partially, and 1 for yes. Then the total score of the article assessment results is interpreted to determine the eligibility of the article as the quality score in table 5. Articles with fair, good, and very good quality will then be included in the analysis stage.

Table 5 Quality Score [13]

Score	Quality Scale
< 2	Very Poor
2-2.5	Poor
3-4.5	Fair
5-6	Good
>6	Very Good

Of the ten articles assessed, five articles showed a score of 7 which means they have very good quality, namely articles number 1,2,3,4, and 6. Three articles showed a score of 6.5, namely articles number 7, 9, and 10 with quality still classified as very good. One article, namely article number 5, showed a score of 6 and is still classified as very good quality. The article with the lowest score is article number 8 with a score of 5.5 and is classified as good quality. The quality assessment of the ten selected articles can be seen in table 6 Article Quality Assessment on the next page.

Data Extraction and Analysis

All articles that enter the eligibility stage have article quality that is worthy of entering the next stage, namely data extraction and analysis. The data extraction process focuses on three main parts of the article, namely the abstract, research results, and research discussion. The extracted data is then analyzed to find answers to the research questions that have been created.

3. RESULT AND DISCUSSION

To answer the research questions, coding was carried out on themes related to the research questions, namely challenges, opportunities, principles and approaches.

Opportunities and challenges in implementing climate change education

Opportunities are situations or conditions that can provide benefits if utilized effectively. Identifying opportunities and then taking steps to exploit them is a very important thing to do. The first opportunity for implementing climate change education is the learning environment found in six SLR articles but with different mentions. Four articles directly mention the word learning environment as an opportunity in implementing climate change education and two other articles mention collaboration between stakeholders and organizations [14], political environment, and media [15]. The learning environment is all conditions that can influence the subjects involved in the teaching and learning process, namely teachers and students. The learning environment can be a physical environment such as a place and facilities for learning or non-physical such as support from the family.

The next opportunity for climate change implementation is students and teachers. Both have strategic roles in implementing climate change education. Students are the main subjects who receive knowledge and develop skills, students are also the next generation who have the potential to become agents of change. Teachers are also seen as agents of change who are as important as students as multipliers of knowledge and action [16]. In climate change education it is found that the reality of classroom teaching depends almost exclusively on the teacher's ability to convey this knowledge [15]. Teachers as facilitators do have the opportunity to convey knowledge about the impacts of climate change and mitigation and adaptation measures through innovative approaches that are relevant to students' daily lives.

Table 6 Article Quality Assessment

No	Item	Article Score									
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	Was the article refereed?	1	1	1	1	1	1	1	1	1	1
2	Were the aim(s) of the study clearly stated?	1	1	1	1	1	1	1	1	1	1
3	Were the study participants or observational units adequately described? For example, students' programming experience, year of study etc	1	1	1	1	0,5	1	1	0,5	0,5	1
4	Were the data collections carried out very well? For example, discussion of procedures used for collection, and how the study setting may have influenced the data collected?	1	1	1	1	0,5	1	0,5	0	1	0,5
5	Were potential confounders adequately controlled for in the analysis?	1	1	1	1	1	1	1	1	1	1
6	Were the approach to and formulation of the analysis well conveyed? For example, description of the form of the original data, rationale for choice of method/tool/package?	1	1	1	1	1	1	1	1	1	1
7	Were the findings credible? For example, the study was methodologically explained so that we can trust the findings; findings/conclusions are resonant with other knowledge and experience?	1	1	1	1	1	1	1	1	1	1
	Total Score	7	7	7	7	6	7	6,5	5,5	6,5	6,5
	Quality Scale	Very Good	Very Good	Very Good	Very Good	Very Good	Very Good	Very Good	Good	Very Good	Very Good

Other opportunities are government, curriculum, and science education. The government as a policy maker for the implementation of climate change education, the curriculum as the main guideline for climate change education, and science education as the main basis for understanding the concept of climate change. The government is a policy-making stakeholder [14], government leadership in education includes support for climate change education, professional development, and provision of resources [17].

Challenges, on the other hand, refer to obstacles or barriers faced in achieving goals or taking advantage of existing opportunities. Challenges can arise from a variety of sources, such as changes in the economic environment, legal or regulatory barriers, intense competition, changes in consumer trends or preferences, or internal organizational issues. Challenges must be overcome or confronted in order to optimize existing opportunities. The first challenge identified in the SLR article is teacher competence which includes mastery of the material broadly and deeply (professional competence) and the ability to manage learning to achieve learning objectives (pedagogical competence) [18]. Teachers who do not have a science background and are unable to understand how to address climate change [15], as well as teachers with a science background who have difficulty in project learning, especially connecting learning with action [17], are challenges that must both be faced.

The next challenge that is widely identified is the context of climate change material, which is complex material with a multi-layered topic nature [16] and is related to many fields [19]. In addition, the explanation of climate change material in school textbooks is not well focused and often uses messages that are too powerful and sensational, which is found to be the next challenge [15]. Furthermore, the challenge of climate change education is in the form of appropriate curriculum tools. The curriculum is a set of plans and arrangements regarding objectives, content, and learning materials as well as methods used as guidelines for organizing learning activities to achieve certain educational goals [20]. The curriculum is indeed designed by involving all parties such as students, parents, society, industry, and policy makers. However, the national curriculum is first determined by the government by setting educational standards that aim to provide equal quality education. As in England, the curriculum has been previously determined, is fixed, and is not related to current issues [14]. Including the issue of climate change which has not been integrated into the independent curriculum implemented in Indonesia and other countries such as Austria, teachers are often faced with difficult decisions about where and how long the topic of climate change can be integrated into teaching [16].

The next challenge for climate change education is collaboration between government, business, civil society and the education sector to foster a science-literate society [14]. And the last challenge is the reality of climate change education in the field where climate change is in a transition phase characterized by appearing explicitly in core subjects [17], as well as other realities in the form of gaps between knowledge and skills [19]. Higher education does not always mean or directly increase pro-environmental behavior.

Principles in climate change education

Six principles were found in the implementation of climate change education based on the analyzed SLR articles. The first is improving teacher competency such as teaching skills, teacher confidence [14], developing competency in handling complex climate change topics [21], teacher training programs that should focus more on the professional development of teachers in the field of climate science [16], and provide innovative and modern learning media, for example with digital learning formats that suit young people's preferences and everyday life [19]. The second principle is commitment and cooperation between all parties, namely universities, schools, companies, policy makers, and the wider community as well as cooperation between students with stakeholders and organizations [14], government leadership to support climate change education, especially in teacher professional development and the provision of resources [17], and the commitment of all parties to address climate change [22].

The third principle is the adjustment of the curriculum and teaching tools, adjustments can be in the form of contextualizing the curriculum, changing the curriculum from frightening to full of hope, and making the national benchmarks that have been determined useful [14]. Other adjustments include integrating climate change education with clear guidelines on how to integrate the topic into various subjects [16], as well as restructuring science education by positioning students as important actors for sustainability in the context of science education [23].

The fourth principle is to foster students' environmental awareness, increase high climate awareness at all levels and increase students' interest in nature. Raising students' awareness of the environment is done through education that focuses not only on increasing knowledge but also on action [23], the gap between knowledge and action is seen as an obstacle to successful adaptation to climate change and is particularly visible in young population groups [19]. Increasing climate awareness is done by giving students the competence to identify issues and responsible actions to keep the earth a habitable planet for everyone. While increasing students' interest in nature is done through curriculum adjustments that have been implemented [14].

The fifth principle is to provide knowledge about climate change, especially to clarify the meaning of climate change education. There is still a lot of confusion about what affects the climate and what does not, and how education can promote climate change [14]. Providing knowledge can be in the form of complementing young people's experiences of climate change through direct experiments, field trips, and demonstrations of impacts in the environment [19]. Young people need to have good knowledge about climate change and human influence on climate in order to consciously decide on pro-environmental actions [19].

The final principle is that climate change education must be comprehensive and contextual, comprehensive means covering more than just scientific topics to connect them to issues related to economics, society, values, and social justice [14]. Contextual means connected to relevant issues [14], covering real-world problems [24], community-oriented and not limited to the school environment alone but offering unique opportunities to involve various community actors and unite them to pursue common goals [16]. Science and climate change need to be seen as important and relevant to life, in the classroom science topics are often seen as unrelated to real-world issues [23].

The right approach to use for climate change education in the classroom

The learning approach is a starting point or a point of view towards the learning process, in learning the main variables involved are teachers and students so that the approach to learning is generally divided into two, namely the teacher-oriented approach and the student-oriented approach [25]. In the SLR article, it was found that several appropriate approaches to implementing climate change education that place students as learning subjects who are actively involved in learning are student-oriented approaches. No climate change learning approaches were found using teacher-oriented approaches. The student-oriented approach is based on constructivism theory, which emphasizes that students construct their own knowledge through active interaction with the environment and learning experiences. In constructivism, the role of the teacher is as a facilitator who supports the process of student exploration and reflection so that learning becomes meaningful and contextual [26].

When viewed from the material, the learning approach is also divided into two, namely the contextual approach and the thematic approach. The contextual approach is an approach that helps students see the meaning of their learning by connecting it to the context of everyday life, while the thematic approach is learning in which the material to be learned by students is presented in the form of topics or themes that are considered relevant [25]. Thematic approach can be a single discipline or multidisciplinary approach. In the SLR article, the thematic approach that is suitable for application in climate change education is a multidisciplinary approach, and for the contextual approach, it is found in the SLR article as one of the recommended learning approaches.

Learning approaches that have been proven to be effective in climate change education were found in nine SLR articles, the first of which was the interdisciplinary and transdisciplinary approach. Although the main scientific aspects of climate change are in the disciplines of biology, chemistry, ecology and environmental science, there are other issues such as natural history, sociology and the politics of climate change which fall within the scope of social studies subjects which must be improved through interdisciplinary and transdisciplinary approaches [14]. Both interdisciplinary and transdisciplinary approaches are approaches that use two or more disciplines. The difference is that in the interdisciplinary approach, problem analysis is carried out in parallel, while the transdisciplinary approach offers a specific approach and even basic assumptions for understanding the complex issues being faced [27]. One form of interdisciplinary approach that combines science, technology, engineering, and mathematics is STEM, which is also recommended as a learning approach that provides students with the opportunity to see how the science they are studying is important for their lives and other living things and to spread knowledge to the surrounding environment [23].

The next approach is the contextual approach, climate change is the main real-life scenario. In line with the contextual approach, another suggested approach is the phenomenon-based learning approach which is a holistic approach that encourages students to learn a phenomenon as a complete intensity in a real context [28]. The phenomenon-based approach is also in line with the cross-curricular approach, namely an interdisciplinary approach for all ages (5–25) and levels of education (from elementary school to higher education) [14]. The holistic approach is found in the SLR article as the right approach to use in implementing climate change education [16], the holistic approach aims to help students understand the interconnectedness between various aspects of themselves and their world, so that students can grow intellectually, emotionally, and socially [29]. Next, an inclusive approach was found, which is an education system that provides opportunities for all students who have disabilities and have the potential for intelligence and/or special talents to participate in education or learning in an educational environment together with students in general [30].

The next important learning approach to be implemented is the socio-scientific approach and the emotional approach to climate change. The socio-scientific approach is a learning approach that is oriented towards the context of science and its relationship to social life in society [31], the emotional approach is an intensive approach between teachers and students like counseling guidance that involves interactive and interpersonal communication in opening up problems faced by students in the scope of school and society. The similarity between the two is bringing the social life of society into the context of learning [32].

In addition to the suggested approaches to climate change implementation, these SLR articles also found four recommended learning models to be used with these approaches. Learning models are procedures or steps in the learning process that can be used as a reference to achieve learning objectives [25]. The first is inquiry based learning which involves students in interdisciplinary and intergenerational inquiry projects, designed not only to provide scientific literacy, but also to influence the behavioral dimension by promoting participants' intention to act [33]. Next is problem based learning which is an active learning strategy that has been proven successful in increasing knowledge and influencing attitudes [19]. The project based learning model is also suggested in the SLR article although implementing this project-based science curriculum is challenging in the context of standardized tests, time allocation, large number of students, and difficulty in giving individual grades [23]. The last is the games based learning model as a new didactic method that suits today's student profile and is a more interesting educational method [15]. The game-based approach in the SLR article was also found to be more interesting than the conventional approach [34].

4. DISCUSSION

The SLR studies analyzed included 10 articles published in the last five years in Scopus-indexed scientific journals, which provide a comprehensive overview of the opportunities, challenges, principles, and learning approaches relevant to climate change education. The main focus of this discussion is to integrate these global findings with social, cultural, and educational policy conditions in Indonesia, so that it can provide applicable and contextual recommendations for educational stakeholders in the country. This approach is important considering the unique characteristics of Indonesian education which requires adaptation strategies that are not only based on scientific evidence, but also consider local dynamics and the specific needs of students and teachers in various regions.

Climate change education in Indonesia has six main opportunities that can be utilized effectively based on SLR findings. First, students act as active subjects and agents of change, allowing them to be directly involved in environmental learning and action, thereby increasing social awareness and responsibility. Second, teachers function as facilitators and agents of change who are important in guiding students to understand climate change issues contextually and applicatively. Third, a learning environment that supports contextual learning, both inside and outside the classroom, provides opportunities for students to relate climate change concepts to real experiences around them. Fourth, science education is the main basis for understanding the scientific mechanisms of climate change, so strengthening science material is very necessary. Fifth, the curriculum as the main guideline must be integrated with climate change issues systematically so that learning becomes focused and relevant. Finally, the role of the government as a policy maker and support provider is crucial in providing resources, teacher training, and policies that support the implementation of climate change education as a whole. Synergistically utilizing these opportunities can strengthen the effectiveness of climate change education in Indonesia, for example by developing contextual teacher training programs and involving local communities in environmental learning activities.

The implementation of climate change education in Indonesia faces a number of significant challenges that need to be addressed in order to be effective and sustainable. First, improving teacher competency both in terms of professionalism and pedagogy, because teachers must be able to deliver complex climate change material in a contextual and interesting way for students. Second, the multidisciplinary and complex nature of climate change material demands an integrative and interdisciplinary learning approach, thus requiring the development of appropriate teaching tools. Third, the limited curriculum tools that accommodate climate change issues systematically are still an obstacle, so better adjustments and integration are needed in the national curriculum. Fourth, the lack of effective synergy and cooperation between the government and schools hinders the provision of adequate policy support, training, and resources. Finally, there is a gap between students' theoretical knowledge and the practical skills needed to deal with climate change issues in real terms, which requires a more applicable and experience-based learning model. To address these challenges, practical recommendations include the development of sustainable and contextual teacher training, curriculum revisions that integrate climate change education holistically, and increased collaboration across stakeholders, including the government, schools, and communities. This approach is expected to strengthen teacher capacity and the relevance of learning, while creating an educational ecosystem that supports the transformation of knowledge into real action in mitigating and adapting to climate change in Indonesia.

The principles of implementing climate change education found in this literature study emphasize six important aspects that must be the basis for implementation in Indonesia. First, continuous strengthening of teacher competencies is crucial so that teachers are able to deliver complex climate change material with an effective and contextual pedagogical approach. Second, commitment and collaboration across stakeholders, including schools, universities, government, and communities, are needed to create a supportive and sustainable learning ecosystem. Third, adjustments to the curriculum and teaching materials must be relevant to the local context and actual climate change issues so that learning becomes meaningful for students. Fourth, fostering environmental awareness and pro-environmental attitudes in students is the main focus for forming behaviors that support climate change mitigation and adaptation. Fifth, the delivery of climate change knowledge must be linked to local contextual issues so that students can understand the real impacts and relevance of the material in everyday life. Finally, the integration of related issues such as sustainability and environmental conservation in learning enriches students' understanding holistically. Consistent application of these principles will strengthen the effectiveness of climate change education in Indonesia and support the creation of a generation that is aware of and responsible for the environment

The most appropriate learning approach for climate change education in Indonesia is a student-centered learning approach, which places students as active subjects in the learning process. In addition, contextual and thematic approaches that integrate various disciplines in an interdisciplinary and transdisciplinary manner are very relevant to addressing the complexity of climate change material involving scientific, social, and environmental aspects. Cross-curriculum, phenomenon-based, holistic, socio-scientific, emotional, inclusive, and

STEM approaches can also enrich students' learning experiences by linking learning materials to real situations and local needs. Active learning models such as inquiry-based learning, problem-based learning, project-based learning, STEM, and game-based learning are highly recommended because they encourage engagement, collaboration, and the development of critical and creative thinking skills. Each of these approaches and models must be adapted to the cultural context and resources in Indonesia so that their implementation is effective and sustainable.

5. CONCLUSION

This literature review study successfully identified relevant opportunities, challenges, principles, and approaches in implementing climate change education based on an analysis of 10 articles published in the last five years. These findings emphasize the importance of a strategic and integrated approach in utilizing existing opportunities, such as actively involving students as agents of change, improving teacher competency, creating a supportive learning environment, integrating science education, developing a relevant curriculum, and optimizing the role of the government in supporting the implementation of climate change education. Climate change education requires a collective commitment from all parties, including educators, policy makers, and the wider community, to ensure the creation of a generation that is able to face the challenges of climate change with adequate knowledge, awareness, and skills.

However, significant challenges remain, including lack of teacher training, the complexity of climate change materials, limited curriculum tools, and the need for closer collaboration between government and educational institutions. Student-centered, interdisciplinary, and phenomenon-based learning approaches provide great opportunities to create more meaningful learning experiences. Active learning models such as inquiry-based learning, problem-based learning, project-based learning and game-based learning have also proven effective, although they require thorough preparation.

To support the development of climate change education, several strategic steps are needed in future research. First, in-depth contextual studies need to be conducted through case studies in various regions to explore the implementation of climate change education according to local challenges and needs. Second, cross-disciplinary collaboration must be strengthened by involving various fields of science to develop more holistic learning materials and approaches. Third, further research is needed to evaluate the effectiveness of climate change education in the long term, especially in measuring its impact on changes in student and community behavior. Fourth, policy and curriculum development are important focuses, where in-depth studies are needed to understand how education policies can support the integration of climate change education into the national curriculum systematically. Finally, innovation in learning models must continue to be developed, including exploring the effectiveness of new approaches, such as the integration of digital technology, to increase student engagement in understanding climate change issues.

The implementation of climate change education in Indonesia needs to be carried out through strategic steps that are adaptive and contextual according to local characteristics. First, the active role of students and teachers must be maximized by placing students as directly involved learning subjects and teachers as facilitators who support contextual learning. The development of relevant and sustainable teacher training is essential to improve professional and pedagogical competence in delivering complex climate change material. Furthermore, teaching materials and tools must be adapted to local conditions and systematically integrated into the national curriculum so that learning becomes relevant and meaningful for students. Close cooperation between the government, schools, and other stakeholders needs to be improved to support the provision of adequate resources, policies, and training. In addition, climate change education must be integrated into various subjects and extracurricular activities, and utilize formal and non-formal learning environments to provide contextual and applicable learning experiences. This adaptive and contextual approach is the key to the successful implementation of climate change education in Indonesia, allowing this program to run effectively and sustainably according to diverse local needs and challenges.

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Review Article

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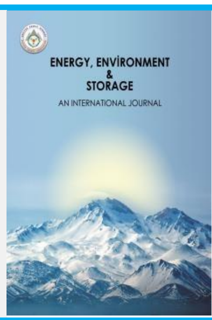

Food Waste in Educational Media: A systematic literature review

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ABSTRACT. Food waste is a critical global issue with significant environmental, economic and social consequences. Educational institutions, as early intervention agents, play a strategic role in fostering sustainable behaviors among students. This systematic literature review aims to explore how interactive learning media have been used to address food waste awareness and behavior in formal education settings. Following the PRISMA protocol, 19 peer -reviewed articles published in the last five years were selected through the Scopus indexed database. The review identified five main themes: awareness, attitude, behavior, media type, and curriculum integration. The results showed that interactive media, such as educational games, digital apps and e-modules, were consistently effective in improving students' awareness and attitudes, although their long-term behavioral impact remains limited without curriculum support. Practical activities and campaign -based interventions also how promising results, but require strategic integration to produce sustainable change. This review contributes to the growing literature by mapping current trends and highlighting the need for more comprehensive and technology -based educational strategies to reduce food waste. Further research is recommended to evaluate the long -term effectiveness and contextual adaptation of these interventions in diverse educational environments.

Keywords: food waste education, interactive learning media, Sustainable Behavior

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1. INTRODUCTION

Food waste has become one of the world's serious global issues, with a total reaching around 1.3 billion tons annually. This amount is equivalent to an economic loss of 940 billion US dollars and has an impact on decreasing food security, environmental degradation, and economic imbalance [1]. Along with greatly increasing greenhouse gas emissions that exacerbate the global climate catastrophe, this phenomena also adds to the waste of natural resources including water, energy, and land [2]

In Indonesia, data from the National Waste Management Information System (SIPSN) in 2024 shows that food waste is the most produced type of waste [3]. This condition reflects an unwise consumption pattern and a lack of reflection of sustainability principles, including within educational environments. The lack of understanding regarding the environmental impacts of food waste, coupled with a consumptive lifestyle, becomes the main cause of this issue [4].

Contextual and interactive education is believed to help students understand the relationship between their consumption behavior and the resulting environmental impacts [5]. Unfortunately, most schools do not yet have food education programs that specifically aim to reduce food waste and improve students' literacy regarding the importance of sustainable food management. Therefore, innovative educational interventions become important to address the root of this problem [6].

Learning can be directed by adopting best practices from countries that have successfully reduced food waste in schools. Japan, for example, offers a model that can be selectively adapted for implementation in Indonesia [7]. Schools have a strategic role in instilling the values of sustainability and wise food management in the younger generation through educational approaches. In this context,

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teachers play an important role. Teachers can be effective catalysts in fostering awareness and encouraging real actions among students toward environmental issues through integrated and participatory learning [8].

The use of creative learning methods, such as utilizing interactive media, has the potential to improve students' understanding of food waste issues. Media such as e-modules, educational games, digital applications, and visual media like Kamishibai have been proven to assist teachers in delivering materials in an engaging and effective manner [9]. However, studies that examine the effectiveness of these media in the context of sustainability education are still limited. Most previous studies have focused more on quantifying food waste or logistical interventions. Meanwhile, the use of digital applications can indeed increase students' awareness of food waste and global environmental issues, although its direct impact on reducing food waste remains insignificant [10].

Based on this background, this study aims to answer two main questions: (1) What are the trends in using interactive media for food waste education in schools?" and (2) To what extent is the effectiveness of interactive media in increasing students' awareness and attitudes toward food waste issues?. Many prior studies emphasize food waste measurement or broad sustainability actions, yet few address how interactive tools function within structured educational contexts. This review addresses that gap by systematically examining how interactive media is utilized to promote food waste education in schools. This systematic literature review is expected to the findings are intended to support educators, curriculum planners, and decision-makers in developing more focused, sustainable, and effective learning strategies related to food waste.

2. MATERIALS AND METHODS

2.1 Methodology

This research utilized the PRISMA guidelines and flowchart. Search engines were used to obtain relevant sources to answer the research question (RQ) and other related references.

2.2 Review Method Identification

The search process was carried out using search engines (ERIC, Scopus, DOAJ and Google Scholar). The initial search process was carried out based on the year of publication in the range 2020 - 2024 using the keywords "FOOD WASTE" AND "STUDENTS" AND "EDUCATION". A summary of the archived articles As shown in Table 1.

Table 1. Initial Search Table

Search Terms	Database	Hits
"FOOD WASTE " AND "STUDENTS" AND "EDUCATION"	Google Scholar	17200
	Scopus	352
	Eric	20
	DOAJ	8

To make sure all pertinent articles had been located, Google Scholar was also employed. The similar search function is not available on Google Scholar term restrictions resulting in 15600 results sortedby relevance [11]. To find undiscovered material, Google Scholar only looked at the top 200 to 300 results. and the first 300 publications' abstracts were examined. There was one article that could not be located that was not found in other databases. The last search was conducted in December 2024.

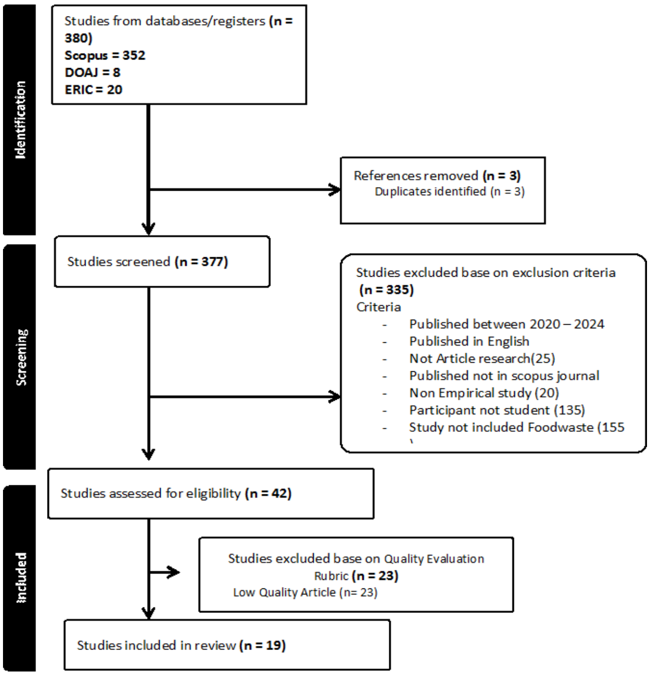

Figure 1. Prism Diagram

Based on Figure 1, in the identification stage, articles sourced from search engines were searched. There are no additional articles from sources other than search. In the screening stage, the same article is eliminated. Furthermore, articles are selected based on the screening of article titles and abstracts. Articles that pass the selection, then enter the eligibility stage. At the eligibility stage, articles are assessed for eligibility based on the specified criteria. At the included stage, 19 articles were found to be reviewable.

The articles were found are selected to the Inclusion and Exclusion Criteria,This stage is carried out to decide whether the data found is suitable for use in SLR research or not. Focusing on articles that met the criteria Inclusion and Exclusion As shown in Table 2.

A rubric was used to assess the quality of each article. The rubric tested seven criteria: purpose, literature review, theoretical framework, participants, methods, results, and conclusions, and significance. Each of the seven sections of the article was evaluated to ensure that they met quality reporting standards [12]. Each of the seven sections is rated on a 4-point scale where 1 = Does Not Meet Standard, 2 = Nearly Meets Standard, 3 = Meets Standard, and 4 = Exceeds Standard. Each article can receive a score ranging from 7 to 28 after adding up the seven sections. Because they did not fulfill the quality standards, articles with scores of 18 or lower were disqualified. Following an evaluation of each article's quality, 15 were kept and four were eliminated. To avoid prejudice, the writers. The assessment quality assessment rubric can be seen in Table 3.

Table 2. Inclusion and Exclusion Criteria

IInclusion Criteria	Exclusion Criteria
Articles published between 2020 and 2024	Articles published before 2020
English language articles	Not English language articles
Articles are based on research	Articles are not the result of research such as proceedings articles or book chapters.
The study was published in a *peer- reviewed journal.*	The study was published not in a journal format
Participants are students up to college-level	Participants who are not students
The study is empirical	The study is not empirical
The study discusses food waste in formal educational environments.	The study did not discuss food waste in formal educational environments.
The study discusses in detail the techniques for educating/researching food waste in educational environments.	The study discusses in detail the techniques for educating/researching students about food waste in educational settings.
The study comes from journals indexed by Scopus.	The study does not come from journals indexed by Scopus.
The extracted data is in line with or answers at least one of the research questions.	The extracted data is not aligned with the research question.

Table 3. quality assessment rubric

Assessment Aspects	4 (Very Good)	3 (Good)	2 (Enough)	1 (Less)
Goals and problems	Problems, objectives, formulated clearly.	Problems, objectives, formulated adequately.	Problems, objectives, formulated less clearly.	Problems, objectives, incompletely.
Literature review	Critically examine field conditions.	Discussing what has and hasn't been done	Discussing at least what has been	Failed to discuss
Theoretical Framework	The theory is explained clearly, and in detail, and the framework is aligned with the study	Theory aligned with objectives.	Theories are not aligned with the objectives.	There is no explanation of the theoretical basis
Participant	Participants were explained in detail and contextually about the population, sample, and sampling procedures.	Participants are explained in detail and contextually about the population, and sample.	Participants have explained the basics	Participants not explained
Method	methodology is well-designed,.	methodology is quite good	methodology has significant weaknesses	methodology is inadequate
Results and conclusions	Data analysis is carried out	The analysis is quite in- depth,	The analysis is shallow and lacks strength	There is no clear analysis or supporting data.
Significance	The article provides new and significant insights *food waste education.*	The article has novelty, but its impact is relatively small.	The article's contribution is minimal	There is no new contribution

3. RESULT AND DISCUSSION

Articles that had a score of 18 or lower on the quality assessment were disqualified for failing to meet the requirements. Following an evaluation of each article's quality, 23 articles were excluded and 19 articles were retained. To prevent bias, the authors made sure that all of the articles that were kept satisfied the requirements by going over the included and excluded articles in light of the criteria.

To make sure the coded quotes fit the context, each theme was examined or checked. The fifth stage was when the themes were identified and categorized, and the sixth step involved writing a report that linked the research questions to the topics. To create the ranking protocol, the authors read the 19 saved articles using the previously created coding protocol using four broad categories: (a) animation (b) science, (c) food waste, and (d) students. After the authors' independent analysis of the first three articles, 45 text passages were taken out and categorized into four Usage:

1. Total Score: Give a score for each aspect (1-4) for each evaluated article.
2. Acceptance Criteria: Define the threshold (e.g., total score
$\geq$18 to include an article).
3. Qualitative Notes: Include comments on specific strengths or weaknesses article.

An intriguing phenomena was discovered and observed when looking at the years of publication of each of the 19 archived articles. Beginning in 2020, the number of papers published on this subject rose annually until 2024, when there were six pieces published. There was 19 articles of research conducted abroad. Namely four from the US, three from China, four from Italy, two from Malaysia, the rest were one article each from Norway, Portugal, Sweden, Denmark, Japan, and Saudi Arabia. 19 studies were conducted, 6 of which were qualitative, 12 were quantitative and 1 used mixed methods. A summary of the archived articles can be found.

3.1 Data Extraction and Synthesis

After going through the process, the data in the articles that meet the inclusion criteria and have good quality will be extracted further to answer the research questions, the extracted data includes basic information on the article (researcher, year of publication, and location of the study), level objectives, learning methods used, Food Waste teaching methods practiced, results, challenges, and opportunities identified and conclusions to be further analyzed Narratively.

Based on 19 articles analyzed in this study, the distribution of publications shows an interesting trend, the articles analyzed were published between 2020 and 2024, with the peak number of publications occurring in 2024 as many as six articles, all articles using a quantitative approach, 6 Qualitative and 1 mixed. An overview of the articles is available in the following table 4.

Author	Title	Participants	Methodology	Findings
Lee 2024	Food waste separation intention among the residential students: Moderating role of university support	191 students in Malaysia	This study collected quantitative primary data from residential students in Malaysia using purposive sampling.	Future research should include comparative studies and incorporate constructs such as trust and incentives to better understand.
Mathisen 2022	The Impact of Smartphone Apps Designed to Reduce Food Waste on Improving Healthy Eating,	6 students from different study programs (Norwegia)	Six students from different study programs evaluated two food waste reduction apps, TotalCtrl Home and Too-Good-To-Go,using mixed methods. the impact of these apps on food waste management.	The study found that app trials increased awareness of food waste, but noted potential for technical and content improvements.
Bathmanathan 2023	What's a waste? An experience in a secondary school in Malaysia of a food waste management system	119 school students (Malaysia)	Researchers conducted meetings with teachers and students. They conducted pre-test and post-test exercises, distributed surveys, and invited	The study aimed to, create a positive attitude towards food waste and ethical behavior.
Malefors 2022	Testing interventions to reduce food waste in school catering	two school canteens, while seven school canteens act as a reference group (Swedia)	The study comprised three main steps (Fig. 1): 1) food waste quantification; 2) design and implementation; 3) post-food waste quantification	Tasting spoons can shift waste from plate to serving fractions, Interventions in Swedish schoolcanteens were successful,
Pandey 2023	Factors influencing consumers' food waste reduction behavior at university canteens	432 respondents from Danish university (Denmark)	The study reveals that attitudes, self-efficacy, and environmental concerns significantly influence food waste reduction behavior...	BMI may also help. This study provides a framework for targeted interventions in university canteens in Denmark.
Piras 2023	Food waste between environmental education, peers, and family influence. Insights from primary school students in Northern Italy	420 Italian primary school students	A lesson on reducing food waste in half of randomly selected classes reduces short-term waste but doesn't persist. Environmental concerns	The message that food waste has negative environmental consequences is passed on but does not result in behavioral change..
Malefors 2024	Automated quantification tool to monitor plate waste in school canteens	Five school dietitians (Japan)	The research team consisted of two US researchers (BTI and CBS) and two Japanese researchers (RA and KF). BTI led the study while she was a Fulbright US Scholar at Ochanomizu University in Tokyo	A global commitment to addressing food waste is crucial for sustainable food systems.
Favuzzi 2020	Evaluation of an alimentary education intervention on school canteen waste at a primary school in Bari, Italy	361 third-grade students. (Italian)	Data was Collected From Canteen attendants, teachers and students using questionnaires.	The study found no significant effect of educational intervention on waste production in school anteens
Fans 2023	FACTORS INFLUENCING FOOD-WASTE BEHAVIORS AT UNIVERSITY CANTEENS IN BEIJING, CHINA: AN INVESTIGATION	University canteen with 705 respondents. (China)	This paper explores factors influencing student food-waste behavior, focusing on sociopsychological, individual characteristics, and dining factors. control, and food portions	Results show that living expenses and food portion size positively influence food waste, while perceived behavioral control, gender, BMI, meal time and meal
Catalano 2024	Food waste awareness among Italian university students: results of an online survey	431 students from the University of Catanzaro Magna Graecia (Italian)	A representative sample of 431 students from the University of Catanzaro Magna Graecia completed an online survey aimed at investigating FW-related behaviors.	Our data suggest that young adults are trying to implement strategies to reduce FW, even if there is room for improvement,
Alsawah 2022	Food Waste, Attitudes and Preferences of Young Women: A Case Study in Saudi Arabia	199 students at Princess Norah Bint Abdulrahman University (Saudi Arabia)	Two indices were calculated to compare and assess the perception of the suggested policies: the Perceived Effectiveness Index (PEI) and the Endorsement Index (EI).	Saudi it does care significantly about food waste and sustainability. The results are encouraging, and further investigations are urgently
Wang 2024	How to Reduce College Students' Food Waste Behavior: From the Perspective of College Canteen Catering Modes	422 consumer College Canteen (China)	A study analyzing 422 valid questionnaires found that food-saving intention and herd mentality are major drivers of college students' food-saving behavior..	Future research should consider the influence of religiosity and family upbringing on food-saving intentions to fill existing literature gaps.
Marques 2022	Impact of a Food Education Session on Vegetable Plate Waste in a Portuguese School Canteen	in 383 primary school meals was evaluated. (Portuguese)	A quasi-experimental study was carried out in a Portuguese school, located in the Guarda district. Data were collected at two different times during January and February in the school year of 2021/2022 and included only primary school students.	The leftover and remaining index of dish vegetable components exceeds literature recommendations, indicating the need for intervention.

Author	Title	Participants	Methodology	Findings
Elnakib 2024	New Jersey Leaves No Bite Behind: A Climate Change and Food Waste Curriculum Intervention for Adolescents	Participants (n = 162) completed pre- and post-test surveys (America)	The study assessed the effectiveness of the NJ Leaves No Bite Behind (NJLNBB) program for fifth-grade students on climate change and food waste. compared to the control group.	There were no significant between-group differences in mean score attitudes, self-efficacy, motivation to comply, or climate-friendly behaviors
Filho 2024	Toward food waste reduction at universities	641 students across disciplines. (America)	This study uses a quantitative and qualitative approach to analyze food waste levels at involving 641 students across disciplines. The research aims to reduce food waste levels by analyzing factors such as gender, age, season, consumer behavior.	Zero waste Universities should invest in converting campus open space into gardens, promoting a culture of waste reduction.
Koetz 2021	Using Extension as a Vehicle to Reduce Elementary Student Food Waste	There were 113 student participants across all eight classrooms (America).	The study taught four treatment classrooms three 1-hour lesson plans over a week. Lessons covered the environmental effects of food waste,	The study found that all treatment groups experienced greater increases in knowledge than control groups, but these were significant only for School 1 second-grade students.
AngelaSciacqua 2024	Food waste awareness among Italian university students: results of an online survey	431 students from the University of Catanzaro Magna Graecia (Italian)	A representative sample of 431 students from the University of Catanzaro Magna Graecia completed an online survey aimed at investigating FW-related behaviors.	The most common type of FW was spoiled fruits and vegetables, followed by meal leftovers and expired products.
HaoFAN 2023	FACTORS INFLUENCING FOOD-WASTE BEHAVIORS AT UNIVERSITY CANTEENS IN BEIJING, CHINA:	China Agricultural University canteen with 705 respondents (China)	Following the survey process, students who came to the cafeteria for lunch and dinner were arbitrarily selected by surveyors and those who agreed to participate in this survey completed a questionnaire after they finished their meal.	Future studies should expand the sample to include students from comprehensive, polytechnic
Oonorasak, 2022	Evaluation of a sustainable student-led initiative on a college campus addressing food waste	Of the 629 students attending the F2F lunch pro (America)	Since evaluation processes play an essential role in the development, implementation, and monitoring of student-driven food	The study supports sustainable efforts to reduce food waste,

3.2 Data Analysis

After explaining in depth the methodology of this study in the previous section, the researcher presents the analysis in this section based on the two research questions that have been identified previously. The research questions are answered in sections 1, 2, and 3 respectively.

1. What are the trends in the use of interactive media in Food Waste Education in the formal education environment?

All extracted data will be analyzed using the Thematic analysis approach [13]. to identify the main themes that answer the research questions: 1) familiarizing yourself with the data by repeatedly reading the extraction results 2) identifying and grouping relevant codes; 3) reviewing and grouping codes into themes; 4) revising and defining the identified themes; 5) compiling the main themes that answer the research questions; 6) reporting the results of a structured thematic analysis.

The researcher read 19 high-quality articles (total rating greater than or equal to 18), so there are four major categories used: (a) Technology-based Interactive Media (b) Direct Methods (c) School-based Campaigns, and (d) Integration into the curriculum The first three articles were analyzed independently by the researcher, and 19 text segments were extracted and placed into one of the four categories, then, the researcher used this four-category protocol to code each of the remaining articles, a total of 50 text segments were extracted and grouped into four major categories. The researcher refined the general codes into sub-codes, namely as shown in Table 5:

Table 5. Pre-established Codes with Refined Sub Codes

Technology-based interactive media	**Direct method through practical activities**
Digital Education Application Educational Animation Video Barcode	Weighing Waste in Schools Observation of Student Consumption Behavior. Collaborative Project Compost Making
School-based campaign	**Integration of sustainability into the curriculum**
Socialization in Schools: Collective Education Involving Parents: The role of families in supporting students' sustainability campaigns.	learning activities to raise awareness of Science and Sustainability Learning in the classroom Use of Interactive Modules Environmental Based Evaluation

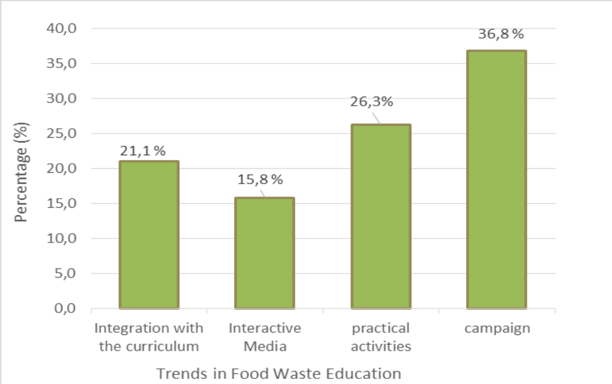

Fig 2. Trends in Food Waste Education

The distribution of aspects of Campaign is the most frequently developed skill at 36,8%, followed by Practical activities 26,3%, integration with the curriculum 21,1%, and practical activities at 15,8%. Among campaign methods (36.8%) and practical activities (26.3%), the use of interactive media in waste education only reached 15.8%. This shows a significant difference in the use of interactive media-based technologies in formal education.

The percentage of campaigns has the highest value (36.8%) because this method is the most widely used, given the absence of material included in classes in schools regarding food waste so the campaign method is the most commonly used regardless of whether this method is effective. followed by practical activities which are the second most after campaigns, practical activities such as the practice of directly weighing food waste generated by individuals, making compost from food waste, and other alternatives specifically, dining facilities on campus and enthusiastic student volunteers who help by picking up waste, preparing food, making compost from waste, and serving food to the community. This study supports ongoing efforts to reduce food wastage [14].

From the graph above Trends in Food Waste shows 21.1%, proving that the concept-based education initiative was not successful in reducing food waste but only impacted students' self-assessment of this behavior in the short term, and this impact was not seen after several months. In turn, the message that food wastage has negative environmental consequences was conveyed to students, and this awareness persisted after a few months, although it did not result in behavior change [15]. with the advancement of the times where students must have technological capabilities that can keep pace with the times, conventional media is no longer in demand although it is still often used in the learning process. this preliminary, descriptive study, we investigated FW-related habits of students enrolled at the University of Catanzaro Magna Graecia in Calabria, a Southern Italian region [16].

The low proportion of interactive media indicates that interactive media is still not the main focus of the food waste education strategy, even though interactive media has great potential to increase student engagement and provide an immersive learning experience. Environmental knowledge has an insignificant impact on food waste sorting intention. Therefore, future research is recommended to include additional constructs that can better capture the unique features of boarding school students' food waste sorting intention to improve the clarity of the research model and produce stronger findings [17]. This suggests that further research is needed to find out how the use of interactive media affects students' awareness and attitude towards food waste in formal learning. Awareness on food waste increased after app trials, but experiences with apps pointed toward several potential for technical and content improvements [18].

2. How effective are interactive media in increasing students' awareness and attitudes towards food waste issues?

Ultimately, the best way to deal with FW is to prevent it in the first place. To achieve this goal, it is imperative to actively engage all students (at every teaching level) in food-growing-focused learning, whether it takes place on campus or not. active in learning that focuses on growing food, whether it takes place on campus or not [19].

The collected articles were analyzed how the educational media affected students' awareness, attitudes and effectiveness. Their effectiveness is summarized in Table 6.

Table 6. effective are interactive media in increasing students' awareness

Author	Media Used	Awareness	Media Effectiveness
Lee, 2024	Food waste separation application by scanning barcode	Understand ing: Increased Caring: Increased	Effective, There is an influence of students' attitudes on their intention to sort food waste.
Mathisen 2022	Too good to go and Totalctrl Home apps	Understand ing: Increased Caring: Increased	Not Effective, There was no significant impact or reduction in food waste across all student group
Bathman athan 2023	Food waste processing practice	Understand ing: Increased Caring: Increased	Effectively, there are more sensitive food waste management behaviors food sharing practices.
Malefor s 2022	Application Tasting spoon	Understand ing: Increased Caring: Increased	Effectively, the tasting spoon has a tendency to transfer waste from the plate waste fraction to the serving waste fraction.
Pandey, 2023	Weighing practice	Understand ing: Increased Caring: Increased	Effective, Research allowing students to weigh their canteen food before purchase can potentially reduce food wastage
Piras, 2023	teaching Food Waste conventionall y in class	Understand i ng: Not Improved Caring: Not Improved	Not Effective, We found that these classroom lessons only reduced self-declared food wastage in the short term,

Malefors , 2024	food waste weighing	Understand ing: Increased Caring: Increased	Effectively, the tool provided students with the opportunity to provide feedback on the reasons behind their food waste.
Favuzzi, 2020	weighing food waste in the school canteen	Understand i ng: Not Improved Caring: Not Improved	Less Effective, This study failed to find a strong impact of the educational intervention on the amount of waste generated in the school canteen.
Fan, 2023	campaign	Understand ing: Increased Caring: Increased	Less Effective, The results showed that there was no significant correlation between behavioral intention to reduce food wastage and behavior
Catalano, 2024	campaign	Understand ing: Increased Caring: Increased	Effectiveness, Conclusion: Our data suggest that young adults are trying to implement strategies to reduce FW, although there is still room for improvement, particularly in the storage phase.
Alsawah 2022	campaign	Understand ing: Increased Caring: Increased	Effectively, the findings improved Saudi people's attitudes towards sustainable behavior and positive attitudes towards food waste recycling.
Wang 2024	campaign	Understand ing: Increased Caring: Increased	Effectively, These results show that students' food saving intention is significantly influenced by their intuitive evaluation of food saving behavior
Marque s 2022	weighing food waste in the school canteen	Understand i ng: Not Improved Caring: Not Improved	Less Effective, lack of control over these parameters and possible explanations for the values obtained
Elnakib, 2024	teaching Food Waste in NJ Leaves No Bite Behind (NJLNBB) class	Understand ing: Increased Caring: Increased	Effectively, the results showed positive outcomes in several key areas. The experimental group, which was exposed to the NJLNBB program,
Filho, 2024	teaching Food Waste conventionall y in class	Understand ing: Increased Caring: Increased	Effectively, the study of food systems has emerged as a major theme of the curriculum
Koetz, 2021	teaching Food Waste conventionall y in class	Understand ing: Increased Caring: Increased	Effective, The survey results reported that all treatment groups experienced a greater increase in knowledge than the control group.
AngelaS ciacqua 2024	food waste campaign	Understand ing: Increased Caring: Increased	Effectively, Interestingly, more than 90% of the entire group reported following the rules for separate waste collection
Oonoras ak, , 2023	campaign	Understand i ng: Not Improved Caring: Not Improved	Less Effective, The results showed no significant correlation between behavioral intention to reduce food waste and behavior.
CanaRoh de 2022	food waste campaign	Understand ing: Increased Caring: Increased	Effective, this case study with operational and evaluation data highlights one of the few campus food programs that tackles food waste.

The above article is processed and a presentation of the assessment results is made and the data is obtained below As shown in Table 7.

Table 7. Percentage Evaluation of Awareness, Attitude, and Media Effectiveness in Food Waste Education"

Teaching Methode	Awareness (%)	Attitude (%)
Integration with the curriculum (4)	75	50
Interactive Media (3)	100	100
practical activities (5)	60	40
campaign (7)	86	86

1. Integration with the Curriculum (4 Literature) Integrating food waste education into the curriculum has proven effective in raising student awareness, with 75% of studies reporting improved understanding. This approach systematically embeds food waste management concepts into daily learning, making it easier for students to grasp the topic. However, only 50% of studies noted changes in students' attitudes, suggesting that awareness alone may not always translate into behavioral shifts. Overall, this method is considered effective, as it provides a consistent framework for introducing and reinforcing food waste concepts.

2. Interactive Media (3 Literature)

Interactive media, such as apps, animated videos, or digital tools, consistently increased awareness in 100% of the studies analyzed. This method effectively engages students, making learning both enjoyable and impactful. Moreover, all studies reported positive changes in attitudes, demonstrating that interactive approaches can successfully encourage behavioral improvements. Interactive media was identified as the effective method, showing consistently high impact in improving awareness, attitudes, and overall effectiveness.

3. Practical Activities (5 Literature)

Practical activities, like weighing food waste or engaging in food management exercises, resulted in increased awareness in 60% of the studies. These hands-on experiences allow students to directly observe and understand the importance of food waste reduction. However, only 40% of studies observed a positive change in attitudes, indicating that practical methods may require additional guidance to foster behavioral changes.

4. Campaigns (7 Literature)

Educational campaigns about food waste were effective in improving awareness and attitudes in 86% of studies. Through repeated messaging and impactful communication, campaigns successfully captured students' attention and inspired them to adopt better behaviors. However, as some limitations were observed in sustaining long-term behavioral changes. These results highlight the potential of campaigns to raise awareness and influence attitudes when combined with supplementary educational methods.

Climate change education often faces challenges in bridging the gap between perception and concrete action [20]. Food waste, in particular, poses a critical challenge with severe environmental and economic consequences, and its prevalence within educational settings raises significant concern [21]. This highlights the need for ongoing development and evaluation of interactive media to enhance its impact on changing student behavior regarding food waste.

Food waste is a major social issue that contributes to the overconsumption of natural resources, hindering economic development and environmental protection [22]. To address this issue, it is essential to design engaging and relevant learning media that can effectively capture students' interest. Both food loss and food waste are pressing concerns due to their detrimental effects on human well-being. One promising approach for educational intervention is the development of interactive digital learning media, such as pop-up e-books [23].

Research has shown that interactive media holds significant potential in increasing students' awareness and understanding of food waste issues. These tools are effective in connecting theoretical knowledge with practical application—an essential component of meaningful learning. Often, students struggle to comprehend complex topics, such as the environmental consequences of food waste, through traditional classroom methods alone. Interactive learning experiences have been found to support deeper understanding of environmental topics [24].

Despite these benefits, the implementation of interactive media continues to face several challenges. In the context of sustainable development, learning tools must continuously evolve to remain relevant and effective [25]. Achieving the Sustainable Development Goals requires reducing food waste at the consumer level [26]. This underscores the importance of collaboration between educators and application developers to produce tools that are both engaging and effective in communicating sustainability messages.

Moreover, many current educational programs yield only short-term results without fostering lasting behavioral change among students. Therefore, it is crucial to develop programs that go beyond delivering information and actively encourage long-term behavioral transformation [27].

Engaging the entire school community—including students, teachers, and parents—in food waste reduction efforts can foster a more sustainable and collaborative learning environment. As global concern about food waste intensifies, researchers are increasingly focused on how to raise awareness among younger generations. Continuous evaluation of how interactive media supports food waste education is essential. Further research is needed to optimize these tools to better meet the needs of students and adapt to local contexts. Thus, this study not only explores the application of interactive media but also identifies areas for improvement to maximize its impact on reducing food waste within educational environments.

Recommendations for practice

The results of this study show some suggestions that can be done to improve food waste education through interactive media. The development of digital interactive E-Modules could be the top priority developed. Apps such as TotalCtrl Home and Too-Good-To-Go have great potential to improve student knowledge but need additional development to make the features and user interface more attractive and easy to use [7]. Therefore, in the future it is hoped that technology can enter the realm of formal education in food waste education for students. Collaboration between various application parties is very important to create application-based E-modules that are not only useful but also fun. Secondly, interactive media can be integrated into the curriculum. This way, students can understand the impact of food waste in a broader context and relate it to everyday life [16]. Third, continuous evaluation of existing educational programs is essential. Further research is needed to determine how effective these programs are in changing behavior and increasing students' awareness of food waste in the long term. Some literature suggests that young adults are trying to implement strategies to reduce FW, although there is still room for improvement [28]. Over the past few decades, there has been a significant rise in research on attitudes towards food waste and policy preferences that impact sustainability. Nonetheless, the majority of studies on food waste education have been carried out in wealthy nations, with relatively few in developing nations. Investigating food waste and attitudes towards sustainability in developing nations is so crucial [29]. hence Understanding consumer behavior on food waste is becoming increasingly important, given its adverse impact on sustainability[30].

4. CONCLUSION

The findings underscore the necessity for innovative Based on a systematic review of 19 articles, this study concludes that interactive learning media holds substantial potential in enhancing students' awareness and attitudes toward food waste issues within formal educational settings. Tools such as digital applications and educational games consistently demonstrate effectiveness in improving students' understanding and promoting more responsible attitudes regarding food waste management.

Nonetheless, several challenges remain, particularly in the development of more user-friendly features and interfaces for interactive media. Some educational programs still lack long-term impact and fail to bring about sustained behavioral change. Therefore, it is crucial to integrate interactive media comprehensively into the curriculum while adapting it to students' needs and local educational contexts.

Curriculum-based food waste education has proven effective in raising awareness, though its influence on shaping students' attitudes and behaviors remains limited. Practical learning activities provide meaningful experiences but are not consistently effective in driving attitude transformation. Campaign-based interventions show strong outcomes in enhancing awareness and attitudes, yet they often require support from other educational methods to achieve lasting behavioral change.

This review recommends prioritizing the development of interactive learning media—such as digital e-modules—as a strategic approach to food waste education. Furthermore, continuous evaluation of existing educational programs is necessary to measure their effectiveness in fostering behavioral change. The insights from this review may inform educators and policymakers in designing more effective, sustainable, and contextually relevant educational interventions for addressing food waste in schools.

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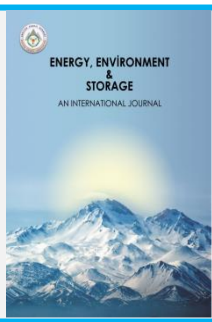

Drought Prediction Based on Global Atmospheric Circulation Indices Using Artificial Neural Networks: A Case for City of Kayseri, Türkiye

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ABSTRACT. Drought is a complex natural phenomenon resulting from prolonged periods of below-average precipitation. Its gradual development over large areas makes it challenging to accurately determine its onset, duration, and overall impact. This study developed an artificial neural network (ANN) method-based model to predict the standard precipitation index (SPI), an index commonly used to determine drought severity. SPI12, which reflects a meteorological drought indicator to monitor precipitation anomalies over 12-month accumulation periods, was estimated based on the artificial neural network (ANN) method using monthly precipitation data recorded in the 1980-2015 period for Kayseri. The North Atlantic Oscillation Index (NAOI), Mediterranean Oscillation Index (MOI), and Arctic Oscillation Index (AOI), which represent large-scale global cycles, were used as input variables in the models. A multilayer perceptron-type ANN model with a single hidden layer was chosen. The model training used 70% of the data and a scaled conjugate gradient backpropagation algorithm. The remaining 30% of the data were used for model testing and control. The activation functions of the ANN model and the number of neurons in the hidden layer were determined using the trial-and-error method. The performances of the models were evaluated using the mean Nash-Sutcliffe coefficient of efficiency (NSE), root mean square error (RMSE), and coefficient of determination (R^2) of agreement between the estimated and observed SPI12 values. This study demonstrated that drought conditions can be successfully predicted 3, 6, and 12 months in advance using indices reflecting large-scale global climate anomalies.

Keywords: Drought, Drought Prediction, Artificial Neural Networks, Precipitation, Standard Precipitation Index

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1. INTRODUCTION

In recent years, due to changing climate characteristics, rapid development of the energy, industry, and agriculture sectors, and population growth, water demand has been steadily increasing, and water shortages are becoming more frequent. The frequency and severity of drought events are changing in many regions of the world. Understanding these changes and predicting future conditions are critical for preventing climate-related disasters.

Drought is a disaster that occurs when precipitation falls below normal levels for many years, causing the deterioration of the hydrological and ecological balance. Predicting the location, time, and duration of a drought event is difficult. Drought differs from other natural phenomena in the sense that it starts very slowly, develops over months or even years, and affects vast areas. It is also challenging to determine the beginning, end, effects, and consequences of droughts.

Various indices have been developed to characterize and monitor drought events. Each of these indices captures different aspects of drought, depending on data availability and the type of drought being studied [1]. Among these, the Standardized Precipitation Index (SPI) is one of the most widely used because of its simplicity, applicability over multiple timescales, and calculability based only on precipitation data.

In this study, we aimed to develop models for predicting drought events characterized by SPI values for Kayseri (Türkiye). We used Artificial Neural Networks (ANN), a machine learning technique that is widely used for

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predicting hydrologic and climatic variables. The input variables for the prediction models include large-scale global oscillation indices representing atmospheric circulation patterns, such as the North Atlantic Oscillation Index (NAOI), Mediterranean Oscillation Index (MOI), and Arctic Oscillation Index (AOI). Prediction models were developed to forecast the SPI12 value, which is the SPI value calculated based on 12-month data. Standard statistical performance metrics were used to evaluate the performances of the developed models.

2. MATERIALS AND METHODS

2.1 Data Used

This study used monthly precipitation data from 1980 to 2015 recorded at the meteorology station number 17196, located in Kayseri. The precipitation data then were used to calculate the SPI values. The SPI [2] was developed to normalize the statistical distribution of precipitation data to eliminate the differences resulting from nonstandard distributions. To calculate the SPI, precipitation data are first fitted to a gamma distribution. The gamma distribution is preferred because precipitation data usually take positive values and have an asymmetric distribution. This fitted gamma distribution was then transformed into a normal distribution using an equal probability transformation. After transformation to a normal distribution, the SPI is expressed as a z-score with zero mean and unit standard deviation. SPI values above zero indicate above-average precipitation, that is, wet periods, whereas SPI values below zero reflect below-average precipitation, that is, dry periods. The SPI allows meteorological drought analysis at different time scales (3, 6, 12, 24, and 48 months). Because the precipitation deficit gradually and variably affects different water resources (e.g., streamflow and groundwater), multiple SPI periods can be used to reflect the changes in different water properties.

Studies conducted in Türkiye have shown that analyzing historical precipitation data, along with large-scale global oscillation indices, is crucial for generating future climate scenarios and predicting drought events [3, 4, 5, 6, 7, 8, 9, 10]. In this study, drought prediction was performed based on SPI12 data and large-scale oscillation indices. The 12-month Standardized Precipitation Index (SPI12) is a meteorological drought indicator that is commonly used to monitor precipitation anomalies over 12-month accumulation periods. It is considered to be a proxy indicator for medium-term hydrological impacts, such as reduced stream flow and reservoir storage.

To describe large-scale atmospheric events, the NAOI, AOI, and MOI, which were previously identified as the most influential indices of precipitation in Türkiye by Dadaser-Celik et al. [11] were considered. The NAOI can be defined as the normalized pressure difference between a station in the Azores and a station in Iceland. The AOI was calculated by reflecting the daily 1000mb height anomalies of the polar oscillation in the poleward direction by 20°K on the loading pattern. The MOI was calculated as the normalized pressure difference between Algiers (36.4°N, 3.1°E) and Cairo (30.1°N, 31.4°E) (MOI1), or between the Northern Border of Gibraltar (36.1°N, 5.3°W) and Israel (32.0°N, 34.5°E) Lod Airport (MOI2). Because MOI1 and MOI2 show similar effects, only the MOI1 index was considered in this study. The time series containing the index data was obtained from the UK Climate Research Unit and the US Climate Prediction Center.

2.2 Model Setup

The model used SPI12 as the output (dependent variable), whereas the inputs (independent variables) included SPI12, NAOI, AOI, and MOI1 values from the preceding 3, 6, and 12 months (Table 1). In other words, the model inputs consisted of historical values of SPI and climate indices (NAOI, AOI, and MOI1) to predict future SPI12 conditions.

A multi-layer perceptron ANN model with a single hidden layer was selected. The model training used 70% of the data and a scaled conjugate gradient backpropagation algorithm. The remaining 15% of the data was used for testing, and the final 15% was used for validation. The data used for the training, testing, and validation were randomly selected. The activation functions of the hidden layer (hyperbolic tangent or sigmoid (S-shaped)) and the number of neurons in the hidden layer were determined using a trial-and-error method. Similarly, the activation functions of the output layer (identity, softmax, hyperbolic tangent, or sigmoid) were selected through trial and error. Additionally, models were run using activation functions with 1–50 neurons in the hidden layer, and the configuration that produced the least error was selected for the study.

The performances of the models were evaluated by calculating the Nash-Sutcliffe efficiency (NSE) coefficient, Root Mean Square Error (RMSE), and Coefficient of Determination (R^2). The NSE coefficient typically ranges between 0 and 1, with values closer to 1 indicating that the model performance has acceptable accuracy. An NSE value of 1 and/or close to 1 signifies that the success of the analysis is high [12]. The R^2 values change between 0 and 1, and values closer to 1 indicate higher performance. For the RMSE, values closer to zero were preferable.

Table 1. Models Inputs and Outputs

Model No	Models Used in the Study
1	$SPI_{t+1} = f(SPI_{(t)}, SPI_{(t-1)}, SPI_{(t-2)}, SPI_{(t-3)})$
2	$SPI_{t+1} = f(SPI_{(t)}, SPI_{(t-1)}, SPI_{(t-2)}, SPI_{(t-3)}, NAO_{(t-1)}, NAO_{(t-2)}, NAO_{(t-3)})$
3	$SPI_{t+1} = f(SPI_{(t)}, SPI_{(t-1)}, SPI_{(t-2)}, SPI_{(t-3)}, AO_{(t-1)}, AO_{(t-2)}, AO_{(t-3)})$
4	$SPI_{t+1} = f\left(SPI_{(t)}, SPI_{(t-1)}, SPI_{(t-2)}, SPI_{(t-3)}, MOI_{(t-1)}, MOI_{(t-2)}, MOI_{(t-3)}\right)$
5	$SPI_{t+1} = f(SPI_{(t)}, SPI_{(t-1)}, SPI_{(t-2)}, SPI_{(t-3)}, NAO_{(t-1)}, NAO_{(t-2)}, NAO_{(t-3)}, AO_{(t-1)}, AO_{(t-2)}, AO_{(t-3)})$
6	$SPI_{t+1} = f\,(SPI_{(t)}, SPI_{(t-1)}, SPI_{(t-2)}, SPI_{(t-3)}, NAO_{(t-1)}, NAO_{(t-2)}, NAO_{(t-3)}, AO_{(t-1)}, AO_{(t-2)}, AO_{(t-3)}, MOI_{(t-1)}, MOI_{(t-2)}, MOI_{(t-3)})$
7	$SPI_{t+1} = f(SPI_{(t)}, SPI_{(t-1)}, SPI_{(t-2)}, SPI_{(t-3)}, SPI_{(t-4)}, SPI_{(t-5)}, SPI_{(t-6)})$
8	$SPI_{t+1}= f(SPI_{(t)}, SPI_{(t-1)}, SPI_{(t-2)}, SPI_{(t-3)}, SPI_{(t-4)}, SPI_{(t-5)}, SPI_{(t-6)})\,, NAO_{(t-1)}, NAO_{(t-2)}, NAO_{(t-3)}, NAO_{(t-4)}, NAO_{(t-5)}, NAO_{(t-6)})$
9	$SPI_{t+1} = f(SPI_{(t)}, SPI_{(t-1)}, SPI_{(t-2)}, SPI_{(t-3)}, SPI_{(t-4)}, SPI_{(t-5)}, SPI_{(t-6)}, AO_{(t-1)}, AO_{(t-2)}, AO_{(t-3)}, AO_{(t-4)}, AO_{(t-5)}, AO_{(t-6)})$
10	$SPI_{t+1}= f\left(SPI_{(t)}, SPI_{(t-1)}, SPI_{(t-2)}, SPI_{(t-3)}, SPI_{(t-4)}, SPI_{(t-5)}, SPI_{(t-6)}, MOI_{(t-1)}, MOI_{(t-2)}, MOI_{(t-3)}, MOI_{(t-4)}, MOI_{(t-5)}, MOI_{(t-6)}\right)$
11	$SPI_{t+1}= f(SPI_{(t)}, SPI_{(t-1)}, SPI_{(t-2)}, SPI_{(t-3)}, SPI_{(t-4)}, SPI_{(t-5)}, SPI_{(t-6)}, NAO_{(t-1)}, NAO_{(t-2)}, NAO_{(t-3)}, NAO_{(t-4)}, NAO_{(t-5)}, NAO_{(t-6)}, AO_{(t-1)}, AO_{(t-2)}, AO_{(t-3)}, AO_{(t-4)}, AO_{(t-5)}, AO_{(t-6)})$
12	$SPI_{t+1}=f((SPI_{(t)}, SPI_{(t-1)}, SPI_{(t-2)}, SPI_{(t-3)}, SPI_{(t-4)}, SPI_{(t-5)}, SPI_{(t-6)}, NAO_{(t-1)}, NAO_{(t-2)}, NAO_{(t-3)}, NAO_{(t-4)}, NAO_{(t-5)}, NAO_{(t-6)}, AO_{(t-1)}, AO_{(t-2)}, AO_{(t-3)}, AO_{(t-4)}, AO_{(t-5)}, AO_{(t-6)}, MOI_{(t-1)},$ $MOI_{(t-2)}, MOI_{(t-3)}, MOI_{(t-4)}, MOI_{(t-5)}, MOI_{(t-6)})$
13	$SPI_{t+1} = f(SPI_{(t)}, SPI_{(t-1)}, SPI_{(t-2)}, SPI_{(t-3)}, SPI_{(t-4)}, SPI_{(t-5)}, SPI_{(t-6)}, SPI_{(t-7)}, SPI_{(t-8)}, SPI_{(t-9)}, SPI_{(t-10)}, SPI_{(t-11)}, SPI_{(t-12)})$
14	$SPI_{t+1}= f(SPI_{(t)}, SPI_{(t-1)}, SPI_{(t-2)}, SPI_{(t-3)}, SPI_{(t-4)}, SPI_{(t-5)}, SPI_{(t-6)}, SPI_{(t-7)}, SPI_{(t-8)}, SPI_{(t-9)}, SPI_{(t-10)}, SPI_{(t-11)}, SPI_{(t-12}\,, NAO_{(t-1)}, NAO_{(t-2)}, NAO_{(t-3)}, NAO_{(t-4)}, NAO_{(t-5)}, NAO_{(t-6)},$ $NAO_{(t-7)}, NAO_{(t-8)}, NAO_{(t-9)}, NAO_{(t-10)}, NAO_{(t-11)}, NAO_{(t-12)})$
15	$SPI_{t+1}= f(SPI_{(t)}, SPI_{(t-1)}, SPI_{(t-2)}, SPI_{(t-3)}, SPI_{(t-4)}, SPI_{(t-5)}, SPI_{(t-6)}, SPI_{(t-7)}, SPI_{(t-8)}, SPI_{(t-9)}, SPI_{(t-10)}, SPI_{(t-11)}, SPI_{(t-12)}, AO_{(t-1)}, AO_{(t-2)}, AO_{(t-3)}, AO_{(t-4)}, AO_{(t-5)}, AO_{(t-6)}, AO_{(t-7)}, AO_{(t-8)}, AO_{(t-9)},$ $AO_{(t-10)}, AO_{(t-11)}, AO_{(t-12)})$
16	$SPI_{t+1}= f(SPI_{(t)}, SPI_{(t-1)}, SPI_{(t-2)}, SPI_{(t-3)}, SPI_{(t-4)}, SPI_{(t-5)}, SPI_{(t-6)}, SPI_{(t-7)}, SPI_{(t-8)}, SPI_{(t-9)}, SPI_{(t-10)}, SPI_{(t-11)}, SPI_{(t-12)}, MOI_{(t-1)}, MOI_{(t-2)}, MOI_{(t-3)}, MOI_{(t-4)}, MOI_{(t-5)}, MOI_{(t-6)},$ $MOI_{(t-7)}, MOI_{(t-8)}, MOI_{(t-9)}, MOI_{(t-10)}, MOI_{(t-11)}, MOI_{(t-12)})$
17	$SPI_{t+1}= f(SPI_{(t)}, SPI_{(t-1)}, SPI_{(t-2)}, SPI_{(t-3)}, SPI_{(t-4)}, SPI_{(t-5)}, SPI_{(t-6)}, NAO_{(t-1)}, NAO_{(t-2)}, NAO_{(t-3)}, NAO_{(t-4)}, NAO_{(t-5)}, NAO_{(t-6)}, NAO_{(t-7)}, NAO_{(t-8)}, NAO_{(t-9)}, NAO_{(t-10)}, NAO_{(t-11)}, NAO_{(t-12)},$ $AO_{(t-1)}, AO_{(t-2)}, AO_{(t-3)}, AO_{(t-4)}, AO_{(t-5)}, AO_{(t-6)}, AO_{(t-7)}, AO_{(t-8)}, AO_{(t-9)}, AO_{(t-10)}, AO_{(t-11)}, AO_{(t-12)})$
18	$\mathrm{SPI}_{t+1}=f(SPI_{(t)}, SPI_{(t-1)}, SPI_{(t-2)}, SPI_{(t-3)}, SPI_{(t-4)}, SPI_{(t-5)}, SPI_{(t-6)}, NAO_{(t-1)}, NAO_{(t-2)}, NAO_{(t-3)}, NAO_{(t-4)}, NAO_{(t-5)}, NAO_{(t-6)}, NAO_{(t-7)}, NAO_{(t-8)}, NAO_{(t-9)}, NAO_{(t-10)}, NAO_{(t-11)}, NAO_{(t-12)},$ $AO_{(t-1)}, AO_{(t-2)}, AO_{(t-3)}, AO_{(t-4)}, AO_{(t-5)}, AO_{(t-6)}, AO_{(t-7)}, AO_{(t-8)}, AO_{(t-9)}, AO_{(t-10)}, AO_{(t-11)}, AO_{(t-12)}, MOI_{(t-1)}, MOI_{(t-2)}, MOI_{(t-3)}, MOI_{(t-4)}, MOI_{(t-5)}, MOI_{(t-6)}, MOI_{(t-7)}, MOI_{(t-8)}, MOI_{(t-9)},$ $MOI_{(t-10)}, MOI_{(t-11)}, MOI_{(t-12)})$

3. RESULTS

3.1 Data Characteristics

The data used in this study consisted of precipitation data, SPI12 values calculated from the precipitation data, and large-scale circulation index data. The annual precipitation and the resulting SPI12 values for the 1980-2015 period for the city of Kayseri are shown in Figs. 1 and 2, respectively.

The average annual precipitation in Kayseri for the period 1980-2015 was calculated as 406 mm. The lowest precipitation in the study area occurred during summer, whereas the highest precipitation levels were observed in the spring and winter. The lowest annual average precipitation occurred in 2001, and the highest in 1988. August was the driest month, with an average monthly precipitation of 6.7 mm. The highest precipitation occurred in May, with an average of 57.5 mm.

The SPI12 values range from a minimum of -2.53 to a maximum of 2.72. Dry periods occurred in the years 1981, 1983, 1985, 1990, 1995, 2001, 2002, 2004, 2005, 2006, 2009, and 2014, while wet periods were observed in the years 1987, 1988, 1989, 1991, 1992, 1998, 1999, 2000, 2003, 2007, 2010, 2011, 2012, and 2015.

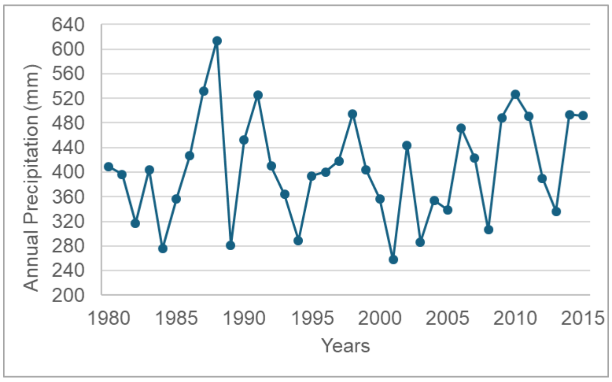

Fig. 1. Annual Precipitation between 1980 and 2015

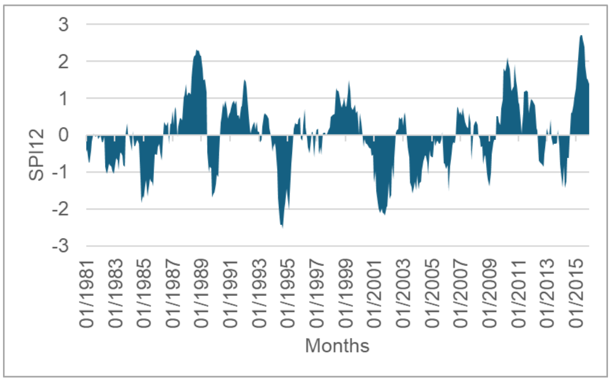

Fig. 2. SPI12 values for the 1981-2015 period

3.2 SPI12 Forecasting Using Data from the Past 3 Months

In the first part of the study, SPI12 values were predicted using the SPI12, NAOI, AOI, and MOI1 values from the past 3 months (Models 1 to 6 in Table 1). The results obtained from predicting SPI12 with different inputs are shown in Figs. 3 and 4. The calculated NSE, RMSE, and R^2 values are presented in Table 2. When data from the past three months were used (Models 1 to 6), Models 3 and 6 were the best-performing models. In Model 3, SPI12 values were predicted using the SPI12 and AOI values in the previous one, two, and three months. In Model-6, SPI12 values were predicted using SPI12, NAOI, AOI, and MOI1 values from the last 1, 2, and 3 months. The NSE, R2, and RMSE values in both models were 0.89, 0.89, and 0.33, respectively. The best model performance was obtained when the hyperbolic tangent was selected as the activation function in the hidden layer and the identity function was used in the output layer.

Table 2. SPI12 Prediction Performance Based on Past 3 Months' Data

Model No	TRAIN			TEST			VALIDATION			ALL		
	NSE	RMSE	R^2	NSE	RMSE	R^2	NSE	RMSE	R^2	NSE	RMSE	R^2
MODEL 1	0.91	0.34	0.88	0.91	0.19	0.82	0.90	0.17	0.90	0.88	0.34	0.89
MODEL 2	0.90	0.35	0.87	0.90	0.21	0.80	0.90	0.17	0.89	0.87	0.36	0.88
MODEL 3	0.91	0.33	0.89	0.91	0.19	0.81	0.92	0.15	0.91	0.89	0.33	0.89
MODEL 4	0.91	0.34	0.88	0.91	0.19	0.81	0.91	0.16	0.90	0.88	0.35	0.88
MODEL 5	0.91	0.34	0.88	0.90	0.20	0.79	0.91	0.16	0.90	0.88	0.35	0.88
MODEL 6	0.91	0.33	0.88	0.91	0.20	0.81	0.92	0.15	0.92	0.89	0.33	0.89

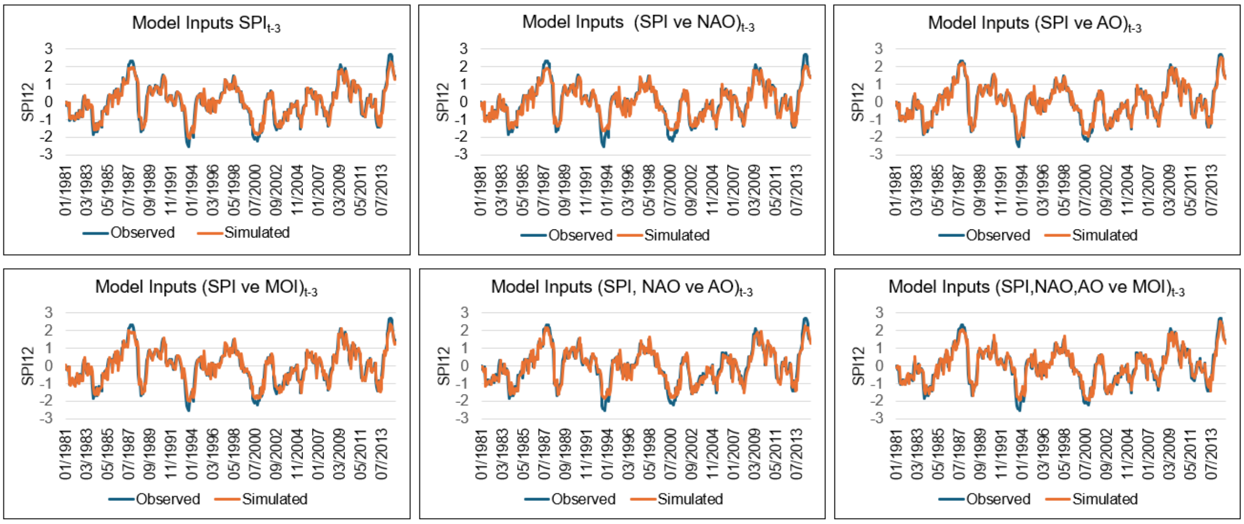

Fig. 3. Observed and Predicted SPI12 Values Based on Past 3 Months' SPI12, NAOI, AOI, and MOI1 Data

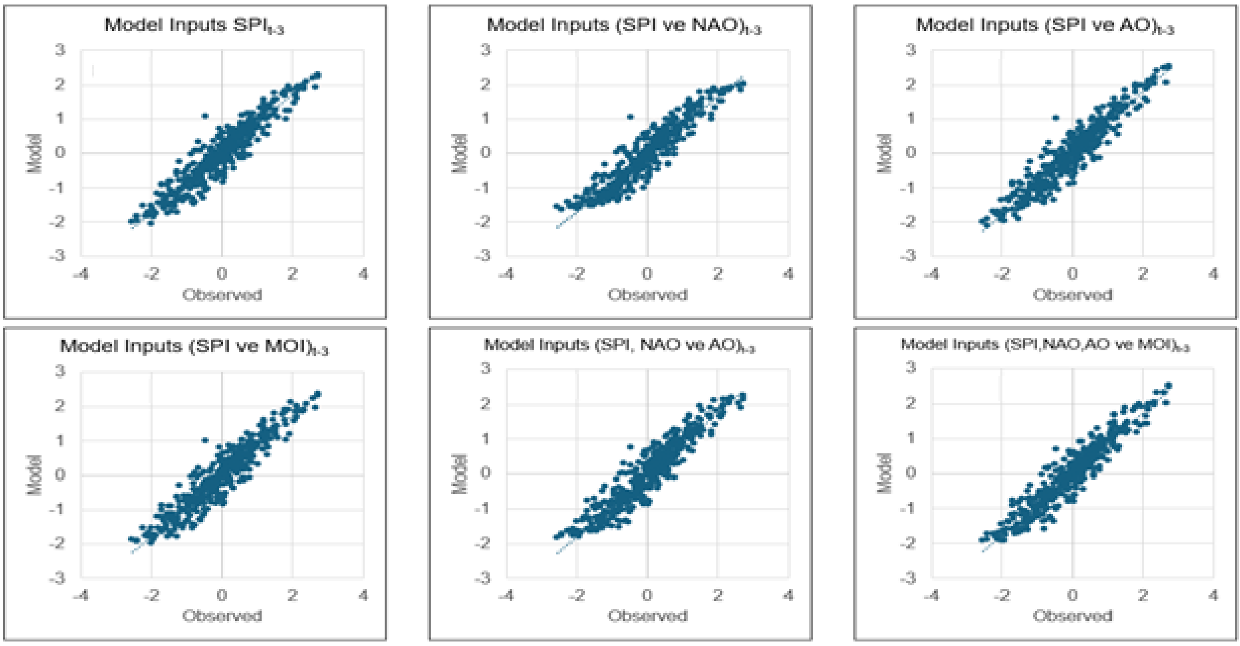

Fig. 4. Correlation of Predicted and Observed SPI12 Values Based on Past 3 Months' SPI12, NAOI, AOI, and MOI1 Data

3.3. SPI12 Forecasting Using Data from the Past 6 Months

In the second part of the study, SPI12 values were estimated using the SPI12, NAOI, AOI, and MOI1 values of the previous 6 months (Models 7 to 12). Fig. 5 and Fig. 6 present the results obtained by estimating SPI12 with different inputs. The correlation analyses of the calculated NSE, RMSE, and R^2 values are presented in Table 3.

When data from the past six months was used as input, the models that provided the best results were Models 9 and 12. In Model 9, SPI12 values were estimated using SPI12 and AOI values from the past six months. Model 12 shows the SPI12, NAOI, AOI, and MOI1 values from the previous 6. In Model 9, the NSE value was 0.90, the R^2 value was 0.90, and the RMSE value was 0.33, whereas in Model 12, the NSE value was 0.91. The R^2 value was 0.92, and the RMSE value was 0.30. The best model performance was attained when the hyperbolic tangent was selected as the activation function in the hidden layer and identity was used in the output layer.

Table 3. SPI12 Estimated Performance Evaluation Based on Past 6 Months' Data

Model No	TRAIN			TEST			VALIDATION			ALL		
	NSE	RMSE	R^2	NSE	RMSE	R^2	NSE	RMSE	R^2	NSE	RMSE	R^2
MODEL 7	0.91	0.34	0.88	0.92	0.19	0.83	0.91	0.16	0.90	0.89	0.33	0.89
MODEL 8	0.92	0.32	0.89	0.93	0.18	0.85	0.92	0.16	0.90	0.88	0.32	0.87
MODEL 9	0.92	0.31	0.90	0.91	0.20	0.81	0.92	0.15	0.92	0.90	0.33	0.90
MODEL 10	0.91	0.34	0.88	0.92	0.19	0.83	0.91	0.16	0.90	0.89	0.34	0.89
MODEL 11	0.86	0.42	0.82	0.89	0.22	0.78	0.87	0.20	0.86	0.83	0.41	0.83
MODEL 12	0.93	0.3	0.90	0.93	0.17	0.86	0.95	0.12	0.94	0.91	0.30	0.92

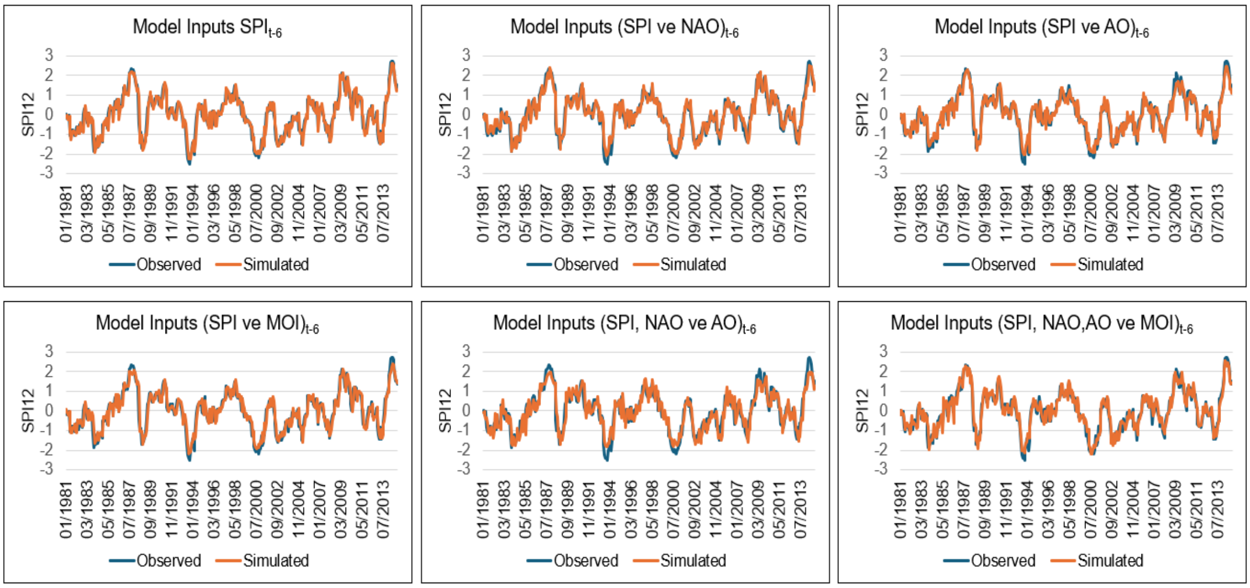

Fig. 5. Observed and Predicted SPI12 Values Based on Past 6 Months' SPI12, NAOI, AOI, and MOI1 Data

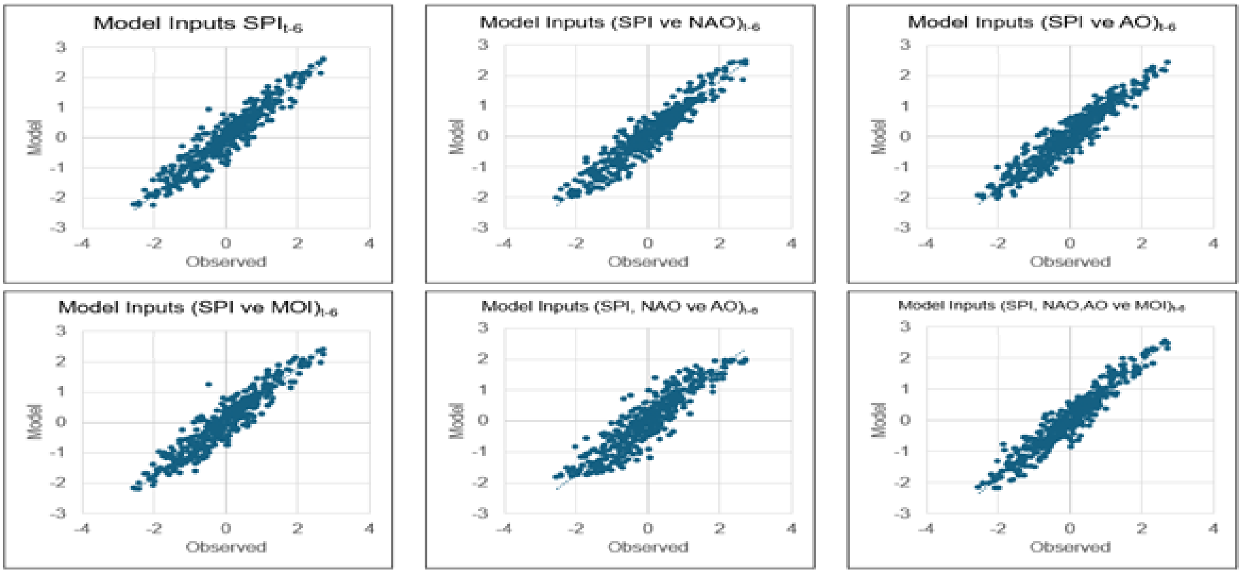

Fig. 6. Correlation of Predicted and Observed SPI12 Values Based on Past 6 Months' SPI12, NAOI, AOI, and MOI1 Data

3.4. SPI12 Forecasting Using Data from the Past 12 Months

In the final part of the study. SPI12 values were predicted using SPI12, NAOI, AOI, and MOI1 data from the past 12 months (Models 13 to 18 in Table 1). The results obtained from predicting SPI12 with different inputs are shown in Figures 7 and 8. The calculated NSE, RMSE, and R2 values are presented in Table 4.

The best-performing models were Models 14 and 15, when data from the past 12 months was used. In Model 14, SPI12 values were predicted using SPI12 and NAOI12 values from the past 12 months. In Model 15, SPI12 values were predicted using SPI12 and NAOI. MOI and AOI values over the past 12 months. In Model 14, the NSE value was 0.91, the R^2 value was 0.91 and the RMSE value was 0.31, while in Model 15. The NSE, R^2, and RMSE values were 0.90, 0.89, and 0.33, respectively.

Table 4. SPI12 Estimated Performance Evaluation Based on Past 12 Months' Data

	TRAIN			TEST			VALIDATION			ALL		
	NSE	RMSE	R^2	NSE	RMSE	R^2	NSE	RMSE	R^2	NSE	RMSE	R^2
MODEL 13	0.92	0.32	0.89	0.92	0.19	0.83	0.91	0.18	0.90	0.89	0.33	0.89
MODEL 14	0.93	0.30	0.91	0.92	0.19	0.84	0.93	0.15	0.92	0.91	0.31	0.91
MODEL 15	0.91	0.34	0.88	0.93	0.18	0.85	0.93	0.15	0.92	0.90	0.33	0.89
MODEL 16	0.91	0.34	0.88	0.92	0.19	0.83	0.89	0.18	0.88	0.88	0.34	0.88
MODEL 17	0.90	0.35	0.87	0.91	0.20	0.83	0.91	0.16	0.90	0.88	0.35	0.88
MODEL 18	0.89	0.37	0.85	0.91	0.19	0.82	0.90	0.17	0.89	0.87	0.37	0.87

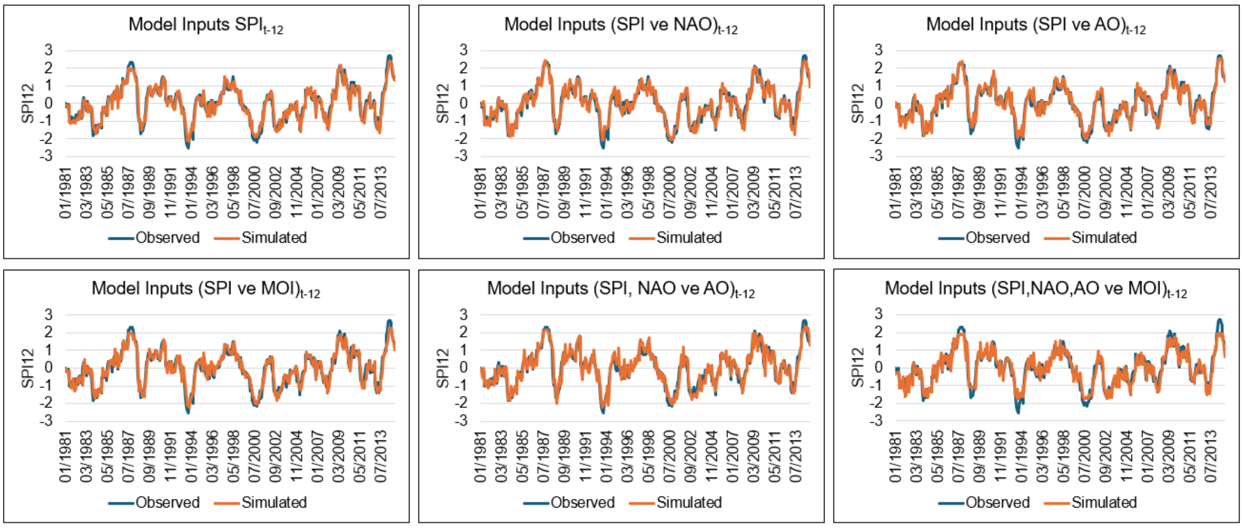

Fig. 7. Observed and Predicted SPI12 Values Based on Past 12 Months' SPI12, NAOI, AOI, and MOI1 Data

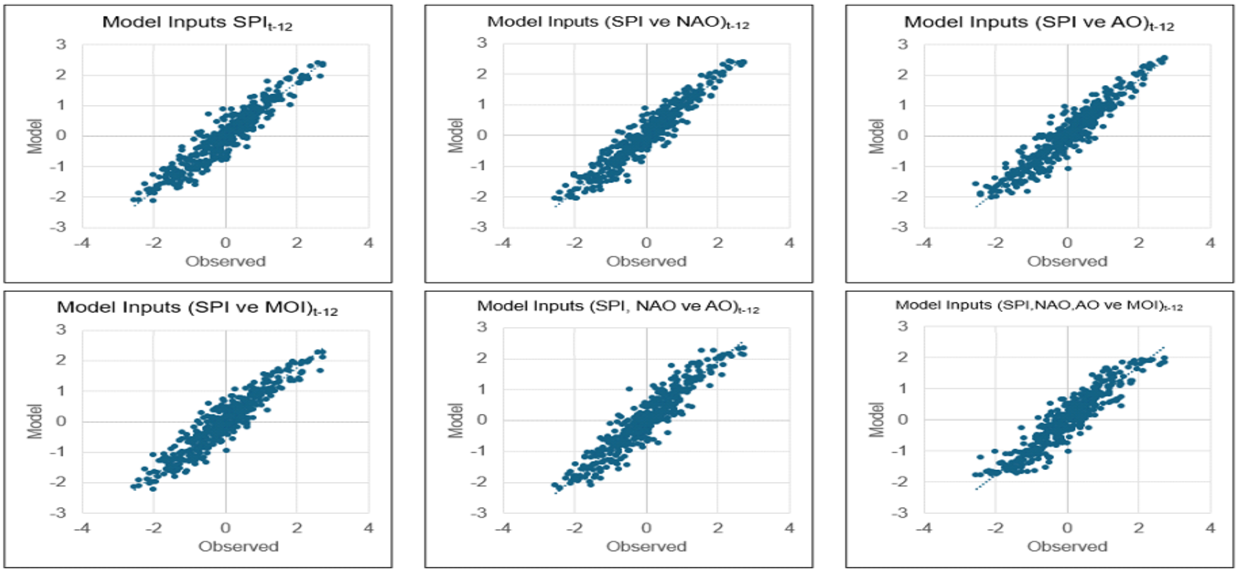

Fig. 8. Correlation of Predicted and Observed SPI12 Values Based on Past 12 Months' SPI12, NAOI, AOI, and MOI1 Data

4. DISCUSSIONS AND CONCLUSION

This study aimed to develop and apply robust and accurate models for drought prediction. Given the complexity and challenges of drought forecasting, it is essential to employ various approaches to capture the nonlinear relationships between drought and meteorological variables. Numerous climatic factors contribute to the occurrence of droughts. The objective was to identify the most effective model or technique for predicting drought under future climate scenarios.

This study developed an ANN model to predict the Standardized Precipitation Index at a 12-month scale (SPI12) using large-scale global climate indices. An Artificial Neural Network (ANN) technique was employed as the modeling approach. The model performance was evaluated using RMSE, R^2, and NSE metrics. In the developed models, SPI12 was used as the dependent variable, while the independent variables included lagged values of SPI12, AOI, NAOI, and MOI1 from the preceding 3, 6, and 12 months.

As a result of the modelling studies, the RMSE values of the SPI12 prediction models ranged from 0.30 to 0.41. The R^2 values ranged from 0.83 to 0.92, and the NSE values ranged from 0.83 to 0.91. The best performance was achieved by Model 12, where the RMSE, $R^{2,}$ and NSE values were 0.30, 0.92, and 0.91, respectively. This result shows that the best prediction performance was obtained when SPI12, NAOI, AOI, and MOI1 values from the preceding six months were used together.

In this study, the ANN method was chosen as the modeling technique. An ANN is a data-driven model that can be used to model complex systems. This method has been used in many studies for SPI prediction [e.g., 13, 14,15]. In this study, using precipitation data, SPI12 values, and large-scale oscillation index data as inputs, the model predicted the SPI12 value with an R^2 value of 0.92 and an RMSE value of 0.30. Similarly, Morid et al. [17] developed a model based on SPI inputs and index values and achieved an R^2 in the range of 0.66-0.79 based on data from the preceding 6 months. Rezaeian-Zadeh [18], incorporating antecedent SPI, precipitation, and both the North Atlantic Oscillation and Southern Oscillation Index, achieved the highest forecasting performance, with an R^2 of 0.92 and an RMSE of 0.35 for 1-month lead time predictions during the validation phase. The performance metric values obtained in this study closely approximate those reported in the literature in magnitude and are at an acceptable level.

This study revealed that large-scale global oscillation indices influence precipitation patterns in Kayseri, and in this sense, the findings agreed with those of the previous studies. The effects of global oscillation indices on precipitation and drought in Türkiye have been demonstrated in previous studies [3, 4, 5, 6, 7, 8, 9, 10, 11] Karabörk et al. [4] analyzed the variability of climate variables in Türkiye based on the Southern Oscillation Index (SOI) and NAOI and showed that NAOI affects precipitation and runoff during winter months. Topuz et al. [10] analyzed annual and seasonal precipitation data from 29 stations in Türkiye between 1955 and 2013. The effect of atmospheric circulation on precipitation variability in Türkiye was investigated using NAOI, MCI, MOI, EMPI, and NCPI. As a result, it was found that the MOI better explained annual precipitation variability in Türkiye than the other indices. Duzenli et al. [9] showed in their study that the NAOI and AOI affect the dry days in all regions of Türkiye, except for the east and northeast during the winter months. Furthermore, when comparing the effects of large-scale global oscillation indices on precipitation extremes and dry days, it was concluded that large-scale global indices significantly impacted the number of dry days. Dadaser-Celik et al. [11], using data from 238 meteorological stations in Türkiye, also showed that large-scale global oscillation indices significantly influence Türkiye's precipitation patterns, and these effects are observed both annually and seasonally.

This study distinguished the potential of predicting SPI using climate indices, precipitation data, and artificial intelligence techniques. It was suggested that new models and scenarios could be developed by adding new data in future studies, and the performance indicators could be improved using such algorithms as deep learning.

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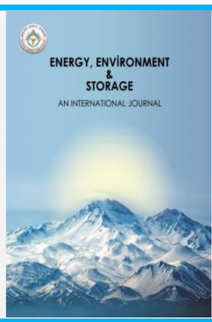

Machine Learning Applications in Biogas and Methane Production: A Bibliometric Analysis

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ABSTRACT. Biogas processes play an important role in the disposal of organic waste. However, these processes are difficult to control because they are highly sensitive and variable. A lot of work has been done to date in order to eliminate this problem. With the development of technology and artificial intelligence, the spread of "Autonomous" systems has become widespread in the control of anaerobic processes as in many other fields. The Anaerobic Digestion Model No. 1 (ADM1) developed by the International Water Association (IWA) has been adopted as the standard model for the AD process since 2002. With the development of this model, Simple Regression Tree (SRT), Probabilistic Neural Networks (PNN), Artificial Neural Networks (ANN), Gradient Boosted Tree (GBT), Linear Regression (LR), Tree Ensemble Regression (TER), Random Forest Regression (RFR), Polynomial Regression (PR), Fuzzy Logic (FL), Adaptive Network-Based Fuzzy İnference System (ANFIS), Different ML algorithms such as Support Vector Machine (SVM), Particle Swarm Optimization (PSO), Genetic Algorithm (GA) Developing Data-Driven Models (DDDV), Deep neural network (DNN) have been used in various studies and tried to perform process optimization, real-time monitoring, disturbance detection and parameter estimation. In this study, the data obtained by using the Bibliometrix package and Biblioshiny package through the R programming language in the R-Studio programme were evaluated. For this purpose, a total of 80 articles in the field of 'Machine Learning' in the Web of Science (WoS) database between 2012-2024 in the fields of 'Biogas Production', 'Methane Production' and 'Anaerobic Digestion' processes were accessed and evaluated. As a result of the evaluations, the development of ML models in biogas processes was determined and recommendations were presented.

Keywords: Anaerobic digestion, ADM1, Autonomous, Bibliometric analiysis, Artifical neural networks

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1. INTRODUCTION

Globally, the primary energy supply still relies heavily on traditional sources such as oil, coal, natural gas, and nuclear energy [1]-[3]. However, due to the limited availability of these resources [4], as well as their contribution to greenhouse gas emissions and environmental pollution [5]-[8], renewable energy sources are increasingly being considered as sustainable alternatives to mitigate the impacts of non-renewable energy use. In recent years, there has been a significant increase in efforts to improve process stability, enhance specific methane yield, and boost economic efficiency [9]-[28]. Anaerobic digestion (AD), a process that converts organic waste into biogas, has gained attention for its ability to support waste-to-energy conversion, promote renewable energy use, and diversify energy supplies in rural areas [29], [30]. Accurate prediction of biogas yield and economic feasibility is essential for the effective implementation of AD systems. However, AD optimization is challenging due to the involvement of numerous physical, chemical, and biological variables [31]. Various approaches have been explored to address these complexities, among which multi-criteria decision-making (MCDM) methods stand out [32], [33]. These methods assign numerical values to alternatives and criteria and use pairwise comparisons to identify the most suitable option [33], [34]. In parallel, machine learning (ML) models have gained significant traction due to their ability to process large datasets, recognize patterns, and offer predictive solutions. ML techniques such as artificial neural networks (ANN) and deep learning (DL) have been widely and successfully applied to model AD processes because of their strong capacity to capture non-linear relationships [16]-[27], [35]-[37], [39]-[45]. This study investigates the development of ML applications in AD through bibliometric analysis and presents novel solution approaches. One of the key innovative aspects of this study is the lack of advanced research using ML to predict the effects of specific microorganisms and their enzyme production capacities on

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AD performance. Although many studies have explored genetically modified microorganisms (GMMs) with enhanced enzyme activity, none have used ML to predict their effects without experimental procedures, which marks another novel contribution of this work. Furthermore, with the rapid advancements in bioinformatics, this study suggests that ML can be used to identify gene regions suitable for intervention (e.g., through cloning) in hydrolytic bacteria and/or methanogenic archaea. This could pave the way for groundbreaking innovations in biogas production, enabling predictive, non-experimental approaches to genetic modifications in AD systems.

In biogas facilities, automation systems are already employed to monitor real-time data such as pH, electrical conductivity (EC), volatile fatty acids (VFA), and especially methane (CH_4) concentration. However, interpreting these data and taking the necessary actions often depend on the experience of the operational staff. In cases where experience is lacking, significant damage to the AD process may occur, leading to time loss, financial setbacks, and reputational damage. To prevent such issues, machine learning can be used to determine key operational parameters—such as hydraulic retention time (HRT), organic loading rate (OLR), and inoculum-to-substrate (I/S) ratio—based on real-time and historical data. This study contributes to the advancement of "Autonomous Biogas Plants" by integrating artificial intelligence into AD systems, aiming to maximize methane production and maintain high operational efficiency continuously.

2. MATERIALS AND METHODS

2.1 Bibliometric Method

Bibliometric studies are highly valuable in identifying new ideas and approaches on relevant topics, developing specific areas of knowledge, identifying gaps, providing an overview of topics, and evaluating publication impact [46]-[48]. In studies, it is possible to examine many factors such as the contributions of the authors, the number of citations, the authors conducting research, the journals in which the articles were published, the countries where the publications were made, and the distribution of keywords by years [47]-[50]. The aim of this study is to evaluate the bibliometric properties of the concept of “Machine Learning” in AD processes in the Web of Science (WoS) database. In this context, the studies on the concept of “Machine Learning” with the keywords “Biogas Production”, “Methane Production” and “Anaerobic Digestion” and published in the WoS database were analyzed according to the years, number of citations, authors and journals, keywords of the publications and the relations of the related keywords with each other. The distribution of the number of citations, categorical clustering analysis and country distributions of the publications on the concept of “Machine Learning” were visualized with the R program and the results of the analysis were evaluated according to the literature. In the research, no year limit was imposed while searching the WoS database. During the search, 3 separate searches were performed using other keywords while keeping “Machine Learning” constant. The 150 articles obtained as a result of the search were examined, and a total of 80 articles related to the subject were identified when the irrelevant and repetitive articles were removed. All other operations were carried out on these 80 articles.

2.2 Machine Learning (ML)

AD processes are very sensitive to changes in the environment. Therefore, monitoring, control and optimization of this process is very difficult [41]. To date, various studies have been carried out to overcome these difficulties in AD processes. However, due to the large number of unknown parameters in these processes, it has been very difficult to increase efficiency or optimize process efficiency. This situation has become even more difficult due to seasonal conditions, substrate variations, especially changes in microbial activities in AD processes due to these variations. This is especially difficult in plants with variable substrate inputs. Therefore, various statistical, mathematical, logical, etc., studies have been carried out to overcome these problems and to maintain the stability/yield of AD processes. However, these traditionally applied methods and mechanistic models have their own difficulties and pitfalls.

Typically, mechanistic models or machine learning (ML) are used to model the AD process [43]. Therefore, it has been proposed by many researchers to build robust data-driven models that facilitate the development of robust data-driven models that utilize and interpret the complex information required for AD processes to function properly. ML has been used in many studies as an alternative method to address these constraints, and as shown in this study, there have been many studies using ML. The first model developed as a product of these studies, the anaerobic digestion model No. 1 (ADM1), is a representative model that simulates AD based on mass balance and kinetics of multiple reactions [51]. The model has been widely used and subjected to some updates to adjust parameters for accurate simulation [52]. The updated ADM1s have been used for methane (CH_4) and volatile fatty acids (VFAs) [53] and digestion of agricultural wastes such as oranges and apples [54] and obtained accurate predictions. However, ADM1-based models have limitations for accurate simulation as the kinetic model depends only on the amount of biomass [42], [55]. Modeling AD plays an important role in monitoring processes and making some predictions.

One way to model the AD process is through a comprehensive mechanistic description of the AD process. Among mathematical models, the Anaerobic Digestion Model No. 1 (ADM1) [51] developed by the International Water Association (IWA) is by far the most comprehensive model used by many researchers [56]-[59]. This model has been adopted as the standard model for the AD process since 2002 [60]-[62]. Initial studies with ADM1, which has been developed into several different models [36], [63]-[66], used a calibrated simulation model of a full-scale biogas plant and showed that the anaerobic digestion process can be predicted with an overall accuracy of 90% [56].

ADM1, which can make accurate predictions of some AD variables such as biogas production and waste concentration [67], [68], describes, with the help of rate equations and model parameters, the main known chemical pathways from the hydrolysis of polymers and monomers to the formation of organic acids, acetic acid, hydrogen and biogas. In addition, ADM1 includes conditions that inhibit the process, such as those related to pH, hydrogen, ammonia and inorganic nitrogen [43]. Besides these advantages, adapting and calibrating ADM1 to various variants of AD processes is a challenge due to limitations in knowledge of microbial consortium composition and complex strain-specific metabolic pathways that require extensive measurements and analyses [51].

Due to these challenges, the development of machine learning (ML) algorithms has become imperative. With the help of ML, process optimization, real-time monitoring, disturbance detection and parameter estimation can be performed [42]. In this context; Simple Regression Tree (SRT), Probabilistic Neural Networks (PNN), Artificial Neural Networks (ANN), Gradient Boosted Tree (GBT), Linear Regression (LR), Tree Ensemble Regression (TER), Random Forest Regression (RFR), Polynomial Regression (PR), fuzzy logic (FL), Different machine learning algorithms such as adaptive network-based fuzzy inference system (ANFIS), support vector machine (SVM), genetic algorithm (GA) and particle swarm optimization (PSO), developing data-driven models (DDDV), Deep neural network (DNN) are used in various studies [17], [23]-[27], [39], [40], [42], [43], [59], [69]-[74]. Such modern machine learning models have the ability to accurately predict the necessary but missing data for AD. For this, model training is first performed with the help of datasets. Then, the resulting model is tested [75] and after these processes, the missing data is predicted [76].

3. RESULT and DISCUSSION

When the data obtained by using the Bibliometrix package and Biblioshiny package through the R programming language in R-Studio were evaluated, a total of 80 articles were reached between 2012-2024 in the field of “Machine Learning” in the “Biogas Production”, “Methane Production” and “Anaerobic Digestion” processes. The 80 articles were written in 35 different journals, by 387 different authors and using a total of 311 keywords. 4708 references were used in the articles. International co-authorship was 45%. No single author was found on the subject and it was determined that the other articles were written by approximately 6 authors (5.51). The top 4 journals in which the articles were published were Chemical Engineering Journal (n:9), Science of The Total Environment (n:8), Journal of Cleaner Production (n:7), Environmental Science and Pollution Research (n:6). Bioresource Technology (n:393) was the most cited journal due to the high number of ML and AD studies, despite not publishing articles directly related to the topic. The most cited country was China with 328 citations and it was found that 9 of the 22 studies prepared by Chinese authors were prepared with the participation of authors from more than one country, and the most cited documents (n:104) were Kim et al., (2020) [77] and De Clercq et al., (2020) [63]. The institution that publishes the most on the subject is Univ Nottingham Malaysia (n:11).

Figure 1 shows the three domain graphs. Through this graph, the 15 authors with the highest number of publications in the field of “Machine Learning” with the keywords “Biogas Production”, “Methane Production” and “Anaerobic Digestion”, the 15 frequently repeated keywords (in the abstracts) and the 15 journals that were most frequently used (most cited) while preparing the studies were visualized. This graph provides information about which keywords the authors use the most and the most influential authors in these studies. The figure shows that Chan yj (impact factor: 145), Zhang y (impact factor: 103) and Wang l (impact factor: 81) are the most influential authors and these three authors were found to be the most influential authors and Bioresource Technology (impact factor: 296), Water Research (impact factor: 296) and Renewable and Sustainable Energy Reviews (impact factor: 296) are the most relevant journals. As a result of the examinations, various methods (ANN, XGBoost, kNN, RF, etc.) were used in studies using machine learning,), various wastes and additives were added (wood waste, microplastics, poultry manure, food waste, Fe_3O_4 additive, animal manure, palm oil wastewater, ZVI (Zero valent iron), Biochar, various predictions (UYA, biogas yield, odor gases, biogas plant operating cost, AD liquid level prediction, ML benchmarking) and microorganism interactions and effects, gene and genome sequences were examined.

When the “Trending Topics” words in the abstract sections of the 80 articles analyzed were examined, it was seen that the first studies with ML started across “biogas plants”. Then, it was determined that especially since 2021, researches were conducted on “biogas production”, “methane yield” and “anaerobic digestion”. In today's studies, it was observed that the keywords “cod removal”, “importance analysis” and “feature importance” were widely used, and studies in which various ML models were tested on AD were emphasized. As can be seen in Figure 2, studies on ML in biogas processes are quite diverse. With the help of interdisciplinary studies, it is aimed to overcome the problems experienced in biogas processes. However, the applicability of ML models in AD processes is still one of the biggest problems today due to access to accurate and sufficient data. In order to overcome these problems, a network should be created and accessibility to “accurate and sufficient” data should be increased by making this information available. In this way, a big step will be taken in the fight against climate change, which is a global problem, regarding the disposal of organic wastes.

With the realization that machine learning (ML) should be applied to improve the efficiency, sustainability and profitability of biogas processes [78], many models have been created and used to control and support AD processes [79], [80].

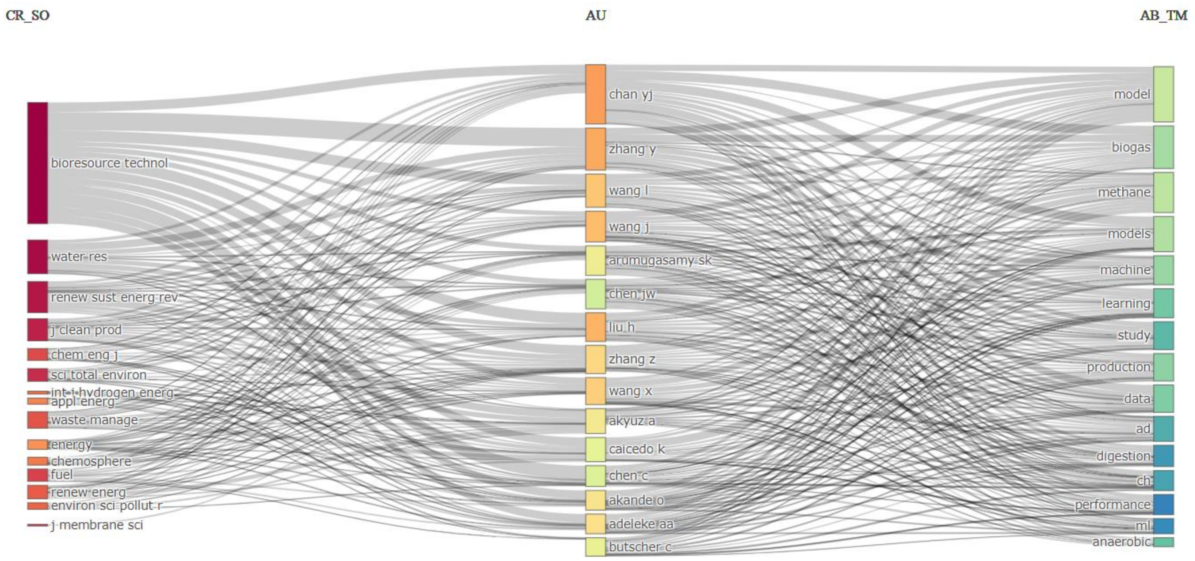

Fig. 1. Three Field Graph

However, early models did not reflect the reality as important parameters such as hydraulic retention time (HRT) [81] and temperature [82] were considered as "constant values" [23]. Many publications cannot provide data on the ten variables (inoculum types, volume (mL), temperature (℃), particle size (mm), inoculum-substrate ratio (according to VS), cellulose content (%), hemicellulose content (%), lignin content (%), digestion time (g), climate and process conditions) selected to create the ML dataset [83], [84]. Therefore, there is a great danger that the data obtained may not reflect the reality.

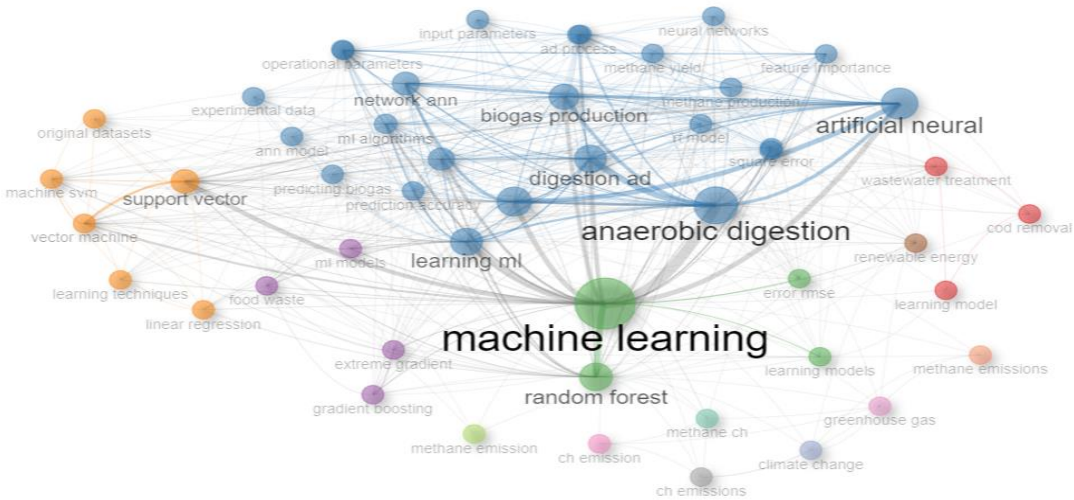

Fig. 2. Co-occurrence Network

In order to optimize the AD process, ML-based models have been applied to many types of wastes and additives [wood waste; [31], microplastic; [89]-[92], poultry manure; [93], food waste; [94], Fe_3O_4 additive [71], animal manure; [40], palm oil wastewater; [25], ZVI (Zero valent iron) [87], Biochar [95], [96], [132], microorganism interactions and effects, gene and genome sequences [33], [36], [52], [65], [88], [92], [97], [105] and various estimates UYA; [52], [106], methane emissions; [73], [74], [107], hydrogen production; [108], biogas/methane yield/production; [13]-[15], [17]-[24], [26], odor gases; [38], biogas plant operating cost; [16], [29], [31], AD liquid level prediction; [41], ML benchmarking; Ling et al., 2024 [42], methane solubility in aqueous phase; [109].

It is understood that for the estimation of biogas production potentials, substrate properties (pH, EC, OM, etc.) are usually estimated with the help of physical and chemical properties such as process temperatures, hydraulic retention times, organic loading rate (Appendix A). The first article identified within the scope of this study was published by Gaida et al. (2012) [56] in 2012. In this article, ADM1 was used and predictions were developed for a full-scale biogas plant with 90% accuracy. Subsequently, Jones and Salter (2013) [79] and Anderson et al. (2013) [80] performed profit/loss analyses of biogas units assuming some values as constant. Pioneered by these studies, other studies have been carried out on AD processes using various wastes and methods. Microorganism, gene and genome studies have accelerated with the advancement of technology and firstly, Vendruscolo et al. (2020) [99] investigated the microbial community structure changes in two biodigesters using metagenome analysis. Subsequently, Long et al. (2021) [36] conducted studies and Yao et al. (2022) [98] developed the "Genomics-enable hybrid" model. In later studies, various studies were carried out using improved ML models and more data. In these studies, 80% of the data were generally used in the training phase and 20% in the testing phase. However, in some studies [13], [16], [76], [96], [108], some of the data were used for "validation". R^2 values were found to be quite high in most of the studies. In some studies, the large amount of data used caused decreases in R^2 values [24], [30], [107]. This proves that it is more important to have appropriate and consistent data rather than a large number of data. The most comprehensive study for Turkey is the study conducted by Pence et al. (2023) [40] in which the animal manure-based biogas potentials of Antalya, Isparta and Burdur provinces located in the Western Mediterranean Region of Turkey were calculated. However, while there are many studies using genetically modified microorganisms (GMMs) whose enzyme production yields are increased by mutations [39], [110]-[131], no study was found to predict the effects of these GMMs with ML without experimentation.

4. CONCLUSION and SUGGESTIONS

Bibliometric analysis is an important convenience in terms of giving researchers an idea about the subject to be analyzed by selecting appropriate keywords. However, when searching the WoS database, if the settings and restrictions are not fully defined, some publications cannot be accessed and some publications that are not related to the subject may be found in the analysis. Therefore, care should be taken when conducting the review. As a result of the reviews, various methods (ANN, XGBoost, kNN, RF, etc.) are used in studies using machine learning,), various wastes and additives were added (wood waste, microplastics, poultry manure, food waste, Fe_3O_4 additive, animal manure, palm oil wastewater, ZVI (Zero valent iron), Biochar, various predictions (UYA, biogas yield, odor gases, biogas plant operating cost, AD liquid level prediction, ML benchmarking) and microorganism interactions and effects, gene and genome sequences were examined. It is also recognized that microorganisms are highly determinant parameters related to AD processes. Although it is known that the enzymes secreted by microorganisms in the hydrolysis, acetogenesis, acidogenesis and methanogenesis stages of AD processes are of vital importance for biogas processes, there is no advanced study on ML to predict the effects of specific microorganisms on AD processes and the positive / negative effects of enzyme production capacity of microorganisms on AD.

One of the other shortcomings is the lack of understanding regarding which physical and/or chemical mutagen affects which gene region, thereby increasing enzyme production capacity (lipase, cellulase, amylase, protease, etc.). Finally, in an era where bioinformatics studies are advancing day by day, monitoring developments in AD processes through cloning studies will allow groundbreaking innovations in biogas processes by enabling the prediction of which gene regions need to be targeted through ML, without the need for experimental studies on controlled changes (cloning, etc.) in the gene regions of hydrolytic bacteria and/or methanogenic archaea.

Using automation systems for real-time monitoring of AD systems, parameters such as pH, EC, TAN, and especially CH_4 can be used to determine HRT, OLR, and I/S ratios via ML [133]-[135]. This allows AI to propose solutions based on real-time data and historical information (obtained through training), thereby maximizing efficiency in AD processes. In "dual systems" where hydrolysis and methane production stages are in separate reactors, monitoring parameters like pH, EC, and TAN of the hydrolysis reactor can help determine the substrate amount (OLR) and hydraulic retention times (HRT) prior to hydrolysis. This ensures that the substrate used in the methane production stage is of high quality and suitable for the highly sensitive methanogenesis stage (with more monomers due to decomposition processes). This will be highly beneficial for sustainable AD processes, maintaining high biogas yields. In reactors where the methanogenesis stage is sustained, the required post-hydrolysis substrate amount can be determined by continuous or intermittent measurements of biogas volume and methane content. Consequently, interventions can be made in the Hydrolysis and Methanogenesis stages based on the information provided by AI trained with ML.

After establishing this system, it is essential to have a deeper understanding of the microorganisms involved for a more sustainable AD process. Metagenomic analyses carried out at certain intervals can closely examine the changes of microorganisms involved in AD processes from a microbiological point of view. Using the data obtained, ML-based predictive models can be developed. This will allow the dosing of hydrolytic bacteria and methanogenic archaea - previously identified and isolated with high enzyme production efficiencies (lipase, cellulase, protease, amylase, etc.) - into AD processes in desired quantities. Consequently, methane yield from AD processes can be maintained at consistently optimal levels, giving rise to the concept of "Autonomous Biogas Plants" empowered by artificial intelligence.

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Python Based Investigation of Compressible Flow Calculations Under Variable Atmospheric Conditions

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ABSTRACT. Flow and thrust calculations at supersonic speeds require intensive formulas and general assumptions, thus prolonging the preliminary design process. Today, the use of computer programs for aerodynamic design and analysis is inevitable in the development of aircraft. However, in this process, traditional calculation methods are mostly used. By performing the relevant calculations with a source code, time-consuming problems such as data extraction from tables, interpolation or calculation with formulas can be avoided. In this study, a computational tool was created in Python using the formulas contained in compressible flow theory. For the calculation, ISA (International Standard Atmosphere) and altitude values are first obtained from the user to determine the atmospheric conditions. These conditions are known to directly affect static conditions. Then, the data input of one of the selected parameters is made and the remaining parameters according to these input values are presented on the result screen together with the other outputs. These outputs were compared with NASA data and their accuracy was analysed. Two different configurations were created to examine the dependence of compressible flow calculations on atmospheric conditions. In the first one, constant ISA and different altitude values were analysed, while in the other one, constant altitude and different temperature deviations were evaluated. These evaluations revealed the sensitivity of the calculation results to atmospheric variables. The findings provide critical data on how to design and analyse aircraft under different operational conditions. This study, for the first time, provides calculations based on atmospheric variables, enabling them to efficiently obtain the values of parameters that depend on these data. This approach is an innovative contribution to the existing literature, expanding the body of knowledge on the analysis of compressible flows.

Keywords: *Compressible Flow, Isentropic Flow, Shock Waves, Atmospheric Conditions, Python*

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1. INTRODUCTION

Isentropic flow is a reversible and adiabatic process with no energy losses. This type of flow is used to study ideal states in aerodynamics and thermodynamics [1]. Shock waves are waves that cause sudden changes in the velocity, pressure, temperature and density of the fluid. They are usually seen in fluids moving at high speeds [2]. Compressible flows occur when the Mach number is greater than 0.3 and under these conditions, the density and other thermodynamic properties of the fluid change significantly [3,4]. These concepts are of critical importance in the fields of aerodynamics and gas dynamics and are used in a wide range of engineering applications [5,6]. One of the most common uses of compressible flows is in aerospace engineering. The aerodynamic design and performance analysis of such vehicles requires a detailed understanding of compressible flow dynamics [7]. Especially for vehicles flying at supersonic and hypersonic speeds, accurate modelling of shock waves and isentropic flows is of great importance [8]. Compressible flow calculations also play a critical role in the design of propulsion systems such as rocket and jet engines. The nozzle designs used in rocket engines are based on isentropic flow principles to achieve maximum thrust [9]. Such engines involve gas dynamics operating at high speeds, and optimizing engine

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performance requires accurate application of compressible flow equations [10]. Another important application of compressible flows is wind tunnel experiments [11]. High speed wind tunnels are used in aerospace engineering tests [12] and compressible flow equations are needed to accurately model the flow conditions in these tunnels [13]. These experiments are used to evaluate the aerodynamic performance and stability of aircraft and spacecraft [14].

Ratios such as P/Pt, T/Tt, etc. used in compressible flow calculations are determined based on Mach and gamma numbers, and in NASA studies in the literature, it was sufficient to know only the Mach number to calculate these ratios [15]. In other words, variable atmospheric conditions such as altitude and ISA were not needed. However, besides the fact that the variability of atmospheric conditions is of great importance for weather forecasts and climate models [13], taking these conditions into account allows for more accurate modelling and calculation of static parameters. This allows compressible flow calculations to obtain more reliable results under variable atmospheric conditions [4]. It is noted that the values of the static parameters can vary greatly under these conditions. Therefore, accurate static parameters are critical for aircraft performance and safety. Accurate determination of these values leads to significant improvements in flight dynamics and aircraft design [7].

In recent years, significant progress has been made in the development of numerical solvers for compressible and incompressible flows within the field of computational fluid dynamics (CFD). In his master's thesis, Kerem Denk developed a two-dimensional, pressure-based Navier–Stokes solver for both compressible and incompressible flows [16]. Similarly, Emre Kara, in his doctoral dissertation, proposed a pressure-based solver for two-dimensional compressible and incompressible flows [17]. In another related study, Semih Akkurt developed a parallel finite volume solver for compressible flows operating on unstructured meshes as part of his master's thesis [18].

The current study aims to be integrated with these solvers and similar CFD development frameworks to achieve more accurate and reliable results. The use of Python, in particular, has become increasingly prevalent in recent years due to the rise of Python-based compressible flow solvers [19,20], which have significantly improved both the accuracy and computational efficiency of such simulations. Among these, the CompAero library [21] stands out as a fundamental reference for modeling compressible aerodynamic analyses using Python.

In this study, the impact of atmospheric conditions on compressible flow behavior is systematically analyzed through two different configurations; novel methods are proposed to model and calculate these effects with greater accuracy.

2. MATERIALS AND METHODS

2.1 Standard Atmosphere Model

For the design process and performance of aircraft, it is important to know the altitude-dependent change information of parameters such as temperature and pressure [22]. Therefore, it is necessary to study the atmosphere at a specific time and place. However, the fact that the real atmosphere is never constant is an obstacle. Therefore, a hypothetical model was used and called the “standard atmosphere”. In the 1920s, the first standard models were developed independently in both Europe and the USA. By 1952, the models were compared and the differences were minimized and a model accepted by the International Civil Aviation Organization (ICAO) was created. The ICAO Standard Atmosphere model was also officially accepted by NACA in the same year [23]. Finally, air -assumed to behave as a perfect gas in the ISA model- can be modeled as follows. In Equations (1)–(6), the temperature T is expressed in degrees Celsius (°C), the altitude h in kilometers (km), and the pressure P in kilopascals (kPa).

Temperature and pressure calculation at altitude up to the troposphere; (0-11 km)

$$T = 15.04 - (0.00649\ x\ h) \tag{1}$$

$$P = 101.29\ x\ \left[\frac{T+273.15}{288.08}\right]^{5.256} \tag{2}$$

Lower Stratosphere; (11-20 km)

$$T = -56.46 \tag{3}$$

$$P = 22.65\ x\ e^{(1.73-0.000157xh)} \tag{4}$$

Upper Stratosphere; (20-47 km)

$$T = -131.21 + (0.00299\ x\ h) \tag{5}$$

$$P = 2.488\ x\ \left[\frac{T+273.15}{216.6}\right]^{-11.388} \tag{6}$$

The given ISA model was used as a reference to compare real atmospheric conditions and the performance of the respective aircraft [24]. In addition to this ISA model, the temperature deviation was also included in the calculations, expressed as +/- ΔISA, to obtain the actual temperature. In this way, the accuracy of the study was increased by running it with real atmospheric data. This is an innovative approach to the literature and allows for a more detailed analysis of the computational results.

2.2 Compressible Flow

The characteristic equations used in the Compressible Flow calculations were compiled from the relevant literature [15,25] and given as equations. These equations were used in Python code and the calculations for the 2 configurations to be examined were performed through this Python code.

It is known that entropy remains constant for isentropic processes [26]. From this, we derive the most general form of the isentropic equations. In Equations (7)-(18), the temperature T and total temperature Tt are given in degrees Celsius (°C). The pressure P and total pressure Pt are expressed in kilopascals (kPa). The density terms ρ and ρt are measured in kilograms per cubic meter (kg/m³). The areas A and A* are in square meters (m²), although they may appear dimensionless in certain ratio-based expressions. The Mach numbers (M, M1, M2) are nondimensional quantities. Angular terms such as the Prandtl-Meyer function (ν), Mach angle (μ), shock wave angle (α), and deflection angle (θ) are expressed in degrees (°). Since most of the equations are ratio-based, many of the resulting terms are dimensionless.

$$\frac{T_t}{T} = \left[\frac{P_t}{P}\right]^{\frac{\gamma-1}{\gamma}} = \left[\frac{\rho_t}{\rho}\right]^{\gamma-1} \tag{7}$$

$$\frac{T}{T_t} = \left[1 + \frac{\gamma-1}{2}M^2\right]^{-1} \tag{8}$$

$$\frac{A}{A^*} = \left[\frac{\gamma+1}{2}\right]^{\frac{-\gamma+1}{2(\gamma+1)}} = \frac{\left[1+\frac{\gamma-1}{2}M^2\right]^{\frac{\gamma+1}{2(\gamma-1)}}}{M} \tag{9}$$

The subscript "t" in the equations stands for "total conditions". The starred conditions are when the Mach number is equal to one. As seen in the equations, once the Mach number is determined, all other parameters are also determined. Likewise, by determining one of the flow parameters (e.g. Temperature Ratio), the Mach number is found and the other parameters can be calculated [15].

The analysis of shock waves is done using Rankine-Hugoniot relations, and these relations play a critical role in understanding the physical and mathematical effects of shock waves. Also, the total temperature remains constant throughout the normal shock [8]. Normal shock equations are given below:

$$M_2^2 = \frac{(\gamma-1){M_1}^2+2}{2\gamma {M_1}^2-(\gamma-1)} \tag{10}$$

$$\frac{T_2}{T_1} = \frac{[2\gamma {M_1}^2-(\gamma-1)][(\gamma-1){M_1}^2+2]}{(\gamma+1)^2{M_1}^2} \tag{11}$$

$$\frac{P_2}{P_1} = \frac{2\gamma {M_1}^2-(\gamma-1)}{(\gamma+1)} \tag{12}$$

$$\frac{\rho_2}{\rho_1} = \frac{(\gamma+1){M_1}^2}{(\gamma-1){M_1}^2+2} \tag{13}$$

$$\frac{P_{t2}}{P_{t1}} = \left[\frac{(\gamma+1){M_1}^2}{(\gamma-1){M_1}^2+2}\right]^{\frac{\gamma}{\gamma-1}} \left[\frac{(\gamma+1)}{2\gamma {M_1}^2-(\gamma-1)}\right]^{\frac{1}{\gamma-1}} \tag{14}$$

$$\nu = \sqrt{\frac{(\gamma+1)}{(\gamma-1)}}\ tan^{-1}\sqrt{\frac{(\gamma-1)}{(\gamma+1)}\left({M_1}^2-1\right)} - tan^{-1}\sqrt{\left({M_1}^2-1\right)} \tag{15}$$

$$\mu = sin^{-1}\left[\frac{1}{M_1}\right] \tag{16}$$

Oblique shock calculations;

$$cot(a) = tan(s)\left[\frac{(\gamma+1){M_1}^2}{2({M_1}^2 sin(s)^2-1)} - 1\right] \tag{17}$$

$${M_2}^2(sin(s-a))^2 = \frac{(\gamma-1){M_1}^2(sin(s))^2+2}{2\gamma {M_1}^2(sin(s))^2-(\gamma-1)} \tag{18}$$

The values of the ratios P2/P1, T2/T1, etc. in the flow of a perfect gas for an oblique shock wave were determined from normal shock relations, provided that M1sin(s) was used instead of M1 and the static temperature T1 just upstream of the shock wave was the same as the normal shock wave for an oblique shock wave [15].

2.3 Method

For this calculation, atmospheric conditions were first determined by taking ISA and altitude. In this way, it was possible to examine the situation under arbitrarily variable atmospheric conditions. Then, the data input of a selected parameter such as M, P, M2, T/Tt, etc. was made and the remaining parameters according to these input values were presented on the result screen together with the other outputs. Python language was used in the study. Thanks to popular libraries such as Pandas and NumPy, data manipulation and visualization is made extremely easy [27, 28]. The interface obtained when the code is run is given in Figure 1. Here the ISA and altitude values are variable. This allowed the current atmospheric conditions to be provided as input. Then one of the parameters was selected and its value or values were entered. If only one value is entered, the result screen is shown in Figure 2, and if more than one value is entered, the result screen is shown in Figure 3.

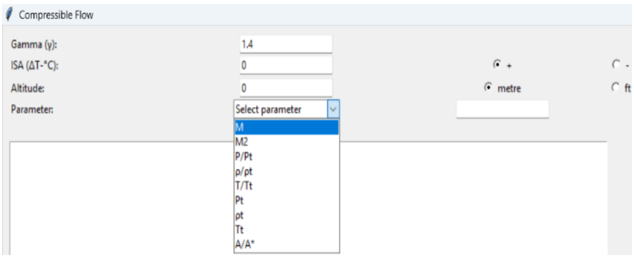

Fig. 1. Application Interface

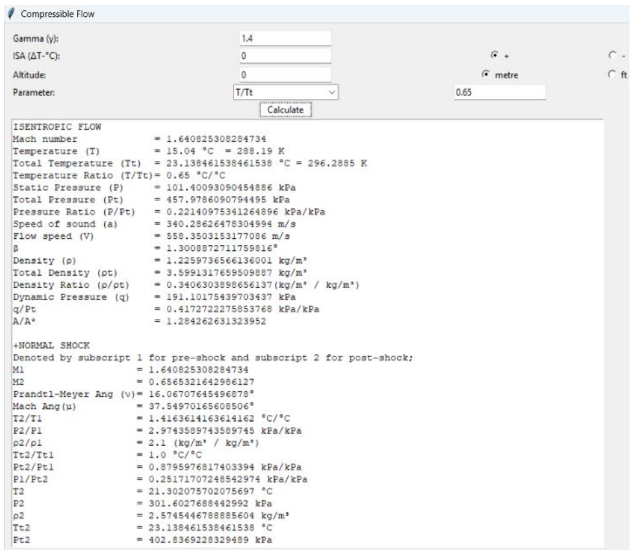

Fig. 2. An Example of an Output Screen When Entering a Single Value

h	0	0	0	0
ISA	0	0	0	0
M	0.1	1	10	100
a (m/s)	340.3	340.3	340.2863	340.286265
V (m/s)	34.03	340.3	3402.863	34028.6265
β (°)	0.995	0	9.949874	99.9949999
T (°C)	15.04	15.04	15.04	15.04
Tt (°C)	15.07	18.05	315.84	30095.04
T/Tt	0.998	0.833	0.047619	0.00049975
P (kPa)	101.4	101.4	101.4009	101.400931
Pt (kPa)	102.1	191.9	4303378	3.6342E+13
P/Pt	0.993	0.528	2.36E-05	2.7902E-12
ρ (kg/m^3)	1.226	1.226	1.225974	1.22597366
ρt (kg/m^3)	1.232	1.934	2477.59	219583074
ρ/ρt	0.995	0.634	0.000495	5.5832E-09
q (kPa)	0.71	70.98	7098.065	709806.516
q/Pt	0.007	0.37	0.001649	1.9531E-08
A/A*	5.822	1	535.9375	46365775.5
M2	-	1	0.387575	0.37806165
ν (°)	-	0	102.3163	127.589813
μ (°)	-	90	5.73917	0.57296734
P2 (kPa)	-	101.4	11813.21	1182993.96
P2/P1	-	1	116.5	11666.5
ρ2 (kg/m^3)	-	1.226	7.005564	7.35216586
ρ2/ρ1	-	1	5.714286	5.9970015
T2 (°C)	-	15.04	306.628	29258.6487
T2/T1	-	1	20.3875	1945.38888
Tt2/Tt	-	1	1	1
Pt2 (kPa)	-	191.9	13102.72	1305644.19
Pt2/Pt1	-	1	0.003045	3.5927E-08

Fig. 3. An Example of an Output Screen When Multiple Values Are Entered

To check the accuracy of the program, the results were compared with the results published by NASA in its 1135 report, and the results were found to be identical [15]. However, in this study, unlike NASA's study, the calculations were not limited to ratios. Thanks to these calculations made by taking into account the variations in atmospheric conditions, static and total conditions were evaluated in addition to the ratios, thus enabling us to present these static and total conditions as results. With this method, a more comprehensive and flexible analysis was presented, taking into account atmospheric variables.

3. DISCUSSION, CONCLUSION, AND RECOMMENDATIONS

3.1 Discussion

Basic parameters such as temperature (T), pressure (P) and density (ρ) vary depending on atmospheric conditions. And these parameters have a direct impact on aircraft performance, engine efficiency and flight safety [29]. The effect of ISA and altitude on these values is critical to understanding how atmospheric conditions change flight dynamics. Variations in temperature and pressure between these layers at different rates have decisive effects on the performance of aircraft [30]. For example, at higher altitudes, lower density and pressure values create less lift on aerodynamic surfaces, while changes in the speed of sound can affect shock wave generation [31]. A detailed analysis of these factors helps to determine operational limits during the aircraft design process [29].

In this study, the effect of atmospheric conditions on compressible flow calculations with different configurations was discussed. In the first configuration, the results were evaluated at constant ISA (0) at different altitudes (0, 10,000, 20,000, 40,000 meters). In the other configuration, the effects of atmospheric parameters on airflow at sea level (0 m) at different ISA deviations (-20, -10, +10 and +20 °C) were analysed. The altitudes selected in the study represent altitudes in different layers of the atmosphere such as troposphere and stratosphere. Static values related to these configurations are calculated with Python code and given in Tables 1 and 2.

Table 1 Configuration 1; altitude-dependent static values only

h(m)	ISA(°C)	T(°C)	a (m/s)	ρ (kg/m³)	P (kPa)
0	0	15.04	340.28626	1.2259736	101.40093
10000	0	-49.86	299.5295	0.413771	26.516206
20000	0	-56.46	295.0695	0.0889185	5.529845
40000	0	-11.61	324.17089	0.00388	0.2913066

Table 2 Configuration 2; static values connected to ISA only

h(m)	ISA(°C)	T(°C)	a (m/s)	ρ (kg/m³)	P (kPa)
0	-20	-4.96	328.266	0.90263	69.47591
0	-10	5.03999	334.33	1.05485	84.21983
0	10	25.04	346.1398	1.41756	121.3161
0	20	35.04	351.8959	1.63126	144.2864

The other parameters affected by these variations also depend on the Mach number. At higher speeds, the effects of these parameters become more complex. Therefore, in order to investigate the variation in these parameters, the study evaluated parameters such as total temperature, flow/vehicle velocity and dynamic pressure over a wide range of Mach numbers under different altitude and ISA conditions. Mach number dependent graphs were created and presented between Figure 4 and Figure 9. The Mach number range considered in the study was chosen as 0-5 in order to evaluate how aircraft behave over a wide speed spectrum, covering subsonic, supersonic and hypersonic flight regimes. In this way, these calculations, performed at different altitudes, at different temperature deviations and over a wide range of Mach numbers, provide vital data for predicting challenges in aircraft design and developing optimal solutions to these challenges [29].

The variation in sound speed and temperature for different configurations are given in Tables 1 and 2. Depending on the atmospheric conditions, the static temperature affects the speed of sound and hence the Mach number. This in turn affects whether the flight is subsonic or supersonic. For example, due to the decrease in the speed of sound at high altitudes, an aircraft flying at the same absolute speed reaches a higher Mach number. This means that supersonic flight will occur earlier (at lower absolute speed) at higher altitudes. This can be advantageous in terms of fuel efficiency and engine design, provided the engine is designed for high altitude conditions. However, due to the low temperatures, changes in material strength and aerodynamic structures need to be considered.

Figure 4 shows a graph of total temperature and aftershock temperature as a function of Mach number under different atmospheric conditions. The graph shows that at higher altitudes, the total temperature generally starts low initially, while at lower altitudes, higher total temperatures are observed initially. This is due to the higher air temperature closer to sea level. When the curves such as Tt, Tt-10, Tt+20 in the graph are analysed, different total temperature values are observed depending on the ISA values. A positive temperature deviation starts the total temperature higher than it actually is, while a negative temperature deviation starts it at lower temperatures. As the Mach number increases, it is observed that the total temperature increases in absolute terms in all total temperature curves. This is because as the Mach number increases, compressible flow effects come into play and convert kinetic energy into temperature [32]. Especially after Mach 2, it is seen that the curves change rapidly, which shows that the temperature change is more pronounced at high speeds. Shock waves and the aerodynamic losses caused by these waves are related to temperature. The effect of shock waves during supersonic flights results in heating and pressure increase on the surface of the aircraft [33]. The increase in Mach number significantly increases the intensity of the shock and the temperature variation. The temperature deviation significantly changed the temperature changes after the shock. With all these, it is generally understood from the graph how much altitude, temperature deviation and speed affect the static and total temperature.

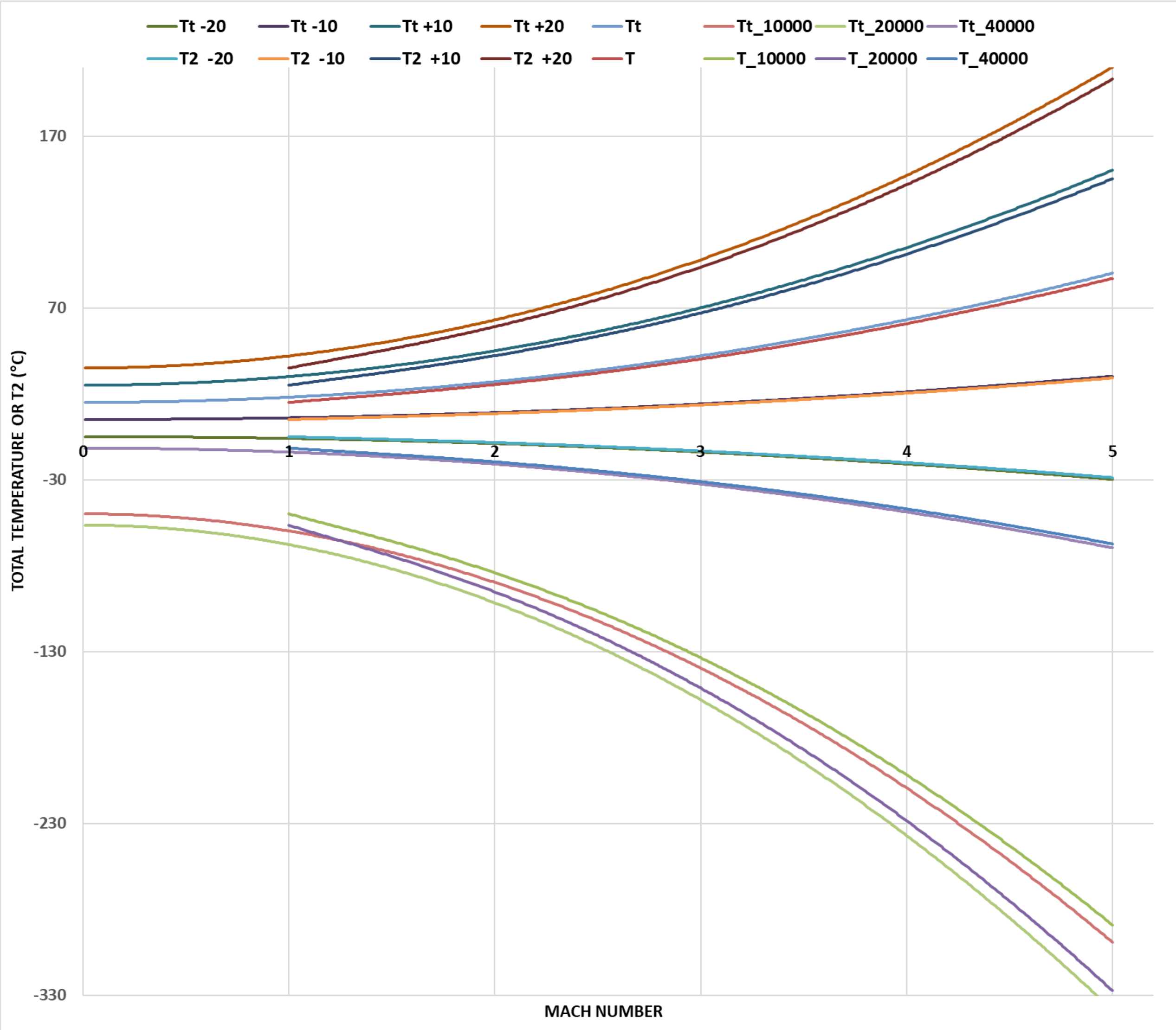

Fig. 4. Mach, Total Temperature, and Static Temperature Graph After Shock for Configurations 1 and 2

Figure 5 shows how the static and total pressure changes with ISA, altitude conditions and Mach numbers after shock formation. The shock wave causes a sudden increase in pressure. At low altitudes, the higher air density causes air compression during the shock wave to create a larger pressure increase. At high altitudes, the air density is lower, so the post-shock pressure increases less. However, pressure spikes were still observed with increasing Mach number. The lower density at high altitudes caused the pressure increase to be more controlled. Warmer air has a lower density, which can reduce the rate of increase in post-shock pressure. But there was still a post-shock pressure increase at supersonic speeds. Since cooler air is denser, the aftershock pressure is higher. This means that there is more compression during the shock wave, which causes the pressure to increase at a greater rate.

The shock wave abruptly reduces the velocity of the flow while increasing other parameters such as pressure, temperature and density. But since these sudden changes are not reversible, energy loss occurs in the flow. This energy loss causes a drop in total pressure. In the graph, the total pressure in the pre-shock flow is generally high, whereas in the post-shock flow it decreases due to friction and the effect of the shock. It was observed that the higher the Mach number before the shock, the greater the total pressure loss after the shock. There is a sudden loss of energy in the flow during the shock wave. These losses are not reversible and the total pressure of the flow is affected by this energy loss. Shock waves usually cause losses due to friction and viscosity. These losses result in the conversion of some of the energy of the flow into heat, which leads to a drop in the total pressure [33].

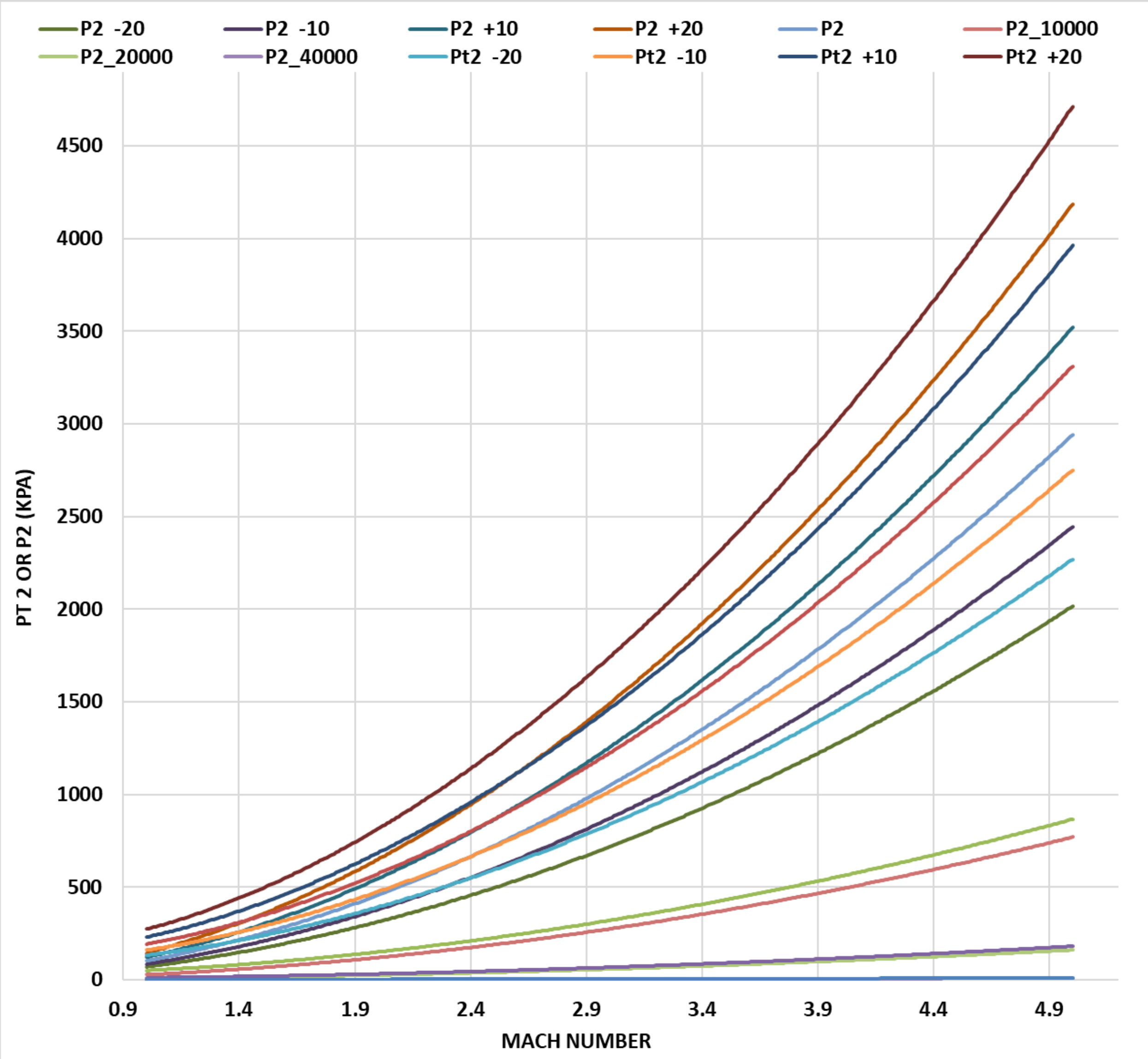

Fig. 5. Mach, Post-Shock Static and Total Pressure Graph for Configurations 1 and 2

Figure 6 shows how the total pressure changes with ISA, altitude conditions and Mach numbers. At lower Mach numbers (between 0 and 1), the increase in total pressure is limited at low speed. This is associated with the velocity regime in which the flow can be considered incompressible. At higher Mach Numbers (especially Mach 3 and beyond), the total pressure increases rapidly as the Mach number increases. Here, it is seen that in the supersonic regime, where the flow becomes compressible, the total pressure increases rapidly due to the effect of shock waves and compression.

In the graph, the total pressure varies at different altitudes. While the highest total pressure values are reached at sea level (approximately 0 meters), these values decrease as the altitude increases. Especially at higher altitudes, the total pressure remains lower. And even if the Mach number increases, the increase in total pressure varies less at high altitudes than at sea level. This is due to the decrease in static pressure with increasing altitude as given in Table 1. Since the air density is lower at higher altitudes, the total pressure naturally decreases. At sea level, the total pressure is considerably higher than the total pressure at other altitudes and rises much faster with the increase in Mach number. The high atmospheric pressure and density at sea level further increases the total pressure at high speeds.

Where the temperature deviation is high, the total pressure is higher than where the temperature deviation is low. In a warm air environment, the total pressure is higher than in other ISA conditions. This is because the air is less dense when the temperature increases. This increases the compression of the flow and has an effect on the total pressure. In colder air, the total pressure is lower. Since cold air is denser, the same Mach number results in lower total pressure.

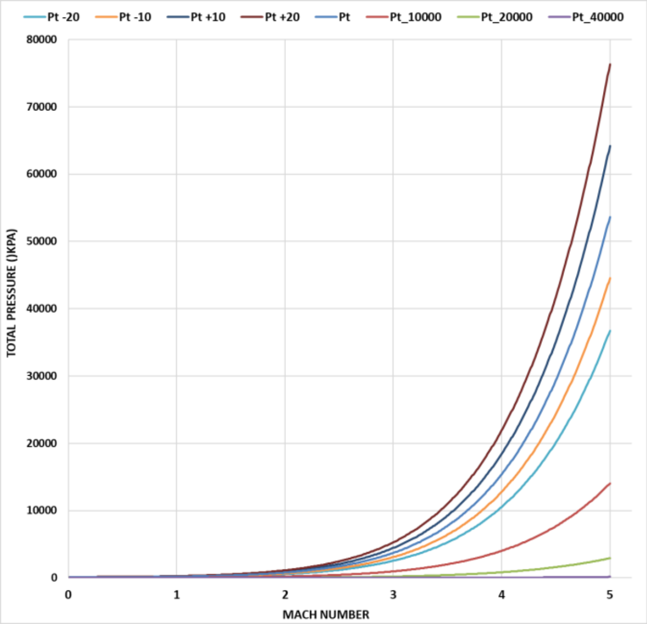

Fig. 6. Mach, Total Pressure Graph for Configurations 1 and 2

Figure 7 shows how the dynamic pressure varies with ISA, altitude conditions and Mach numbers. The dynamic pressure increase is relatively slow at low speeds where the flow can be considered incompressible. From Mach 3 onwards, a rapid increase in dynamic pressure is observed. This is due to the increase in the kinetic energy of the air flow as it accelerates. In this regime, the air becomes compressible and the pressure forces acting on the surface of the aircraft increase significantly. It is observed that the dynamic pressure decreases with increasing altitude. At higher altitudes, the density of the air is lower, so the dynamic pressure reaches lower values at the same Mach number. Different ISA values also affect the dynamic pressure. In warmer air conditions, the dynamic pressure is higher than in other conditions. Although warmer air is less dense, the increase in kinetic energy compensates for this and the dynamic pressure increases rapidly as the Mach number increases. In colder air, the air is denser, so the dynamic pressure is lower at the same speed. Because the air is denser, as the Mach number increases, the dynamic pressure remains lower than in other temperature conditions.

The change in total density at different ISA, altitude and Mach numbers is given in Figure 8. Since these effects change the static temperature, they also change the total density. It can be seen from the graph that the temperature deviation changes the density in a directly proportional way. As the temperature increases, the density of the air decreases because warmer air expands and contains fewer molecules. In colder conditions, the density increases. As altitude increases, atmospheric pressure and temperature decrease, leading to a decrease in air density.

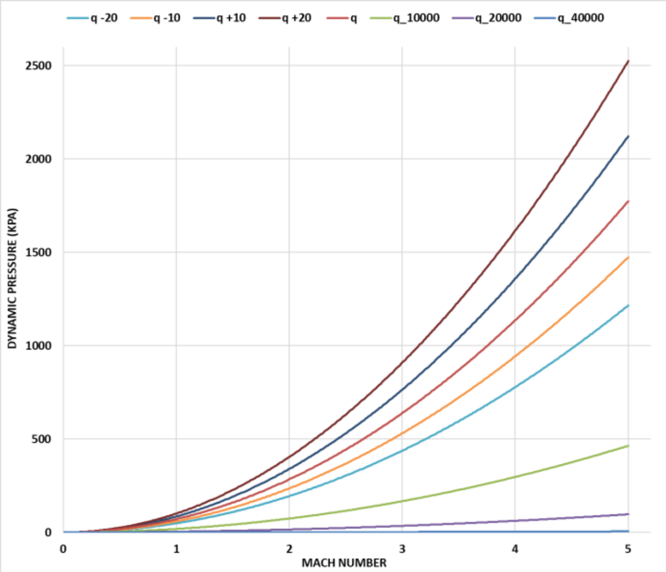

Fig. 7. Mach, Dynamic Pressure Graph for Configurations 1 and 2

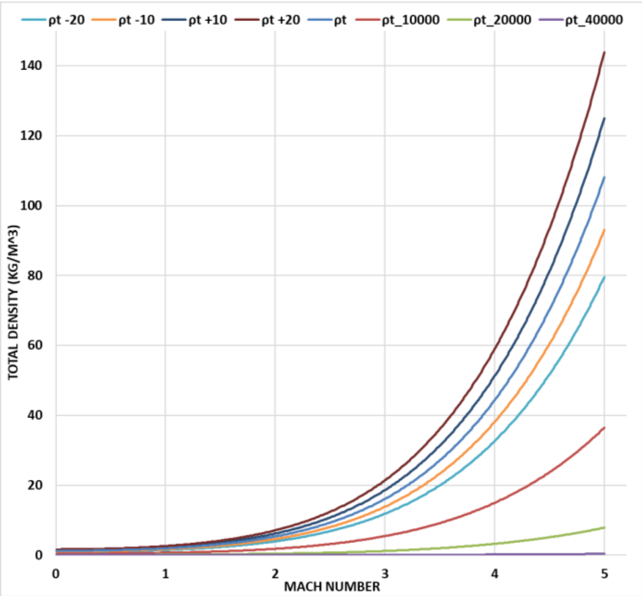

Fig.8. Mach, Total Density Plot for Configurations 1 and 2

The change in static density after the shock at different ISA, altitude and Mach numbers is presented in Figure 9. While the static density before the shock is independent of Mach number, the static density after the shock undergoes significant changes due to the effect of shock waves in compressible flows. While the flow velocity decreases during the shock, the pressure increases after the shock, leading to an increase in density. Despite the increased pressure and temperature values after the shock, the density was more affected by the increase in pressure [34]. It is observed that the density decreases rapidly with increasing altitudes. The temperature deviation changed the total density in a directly proportional manner.

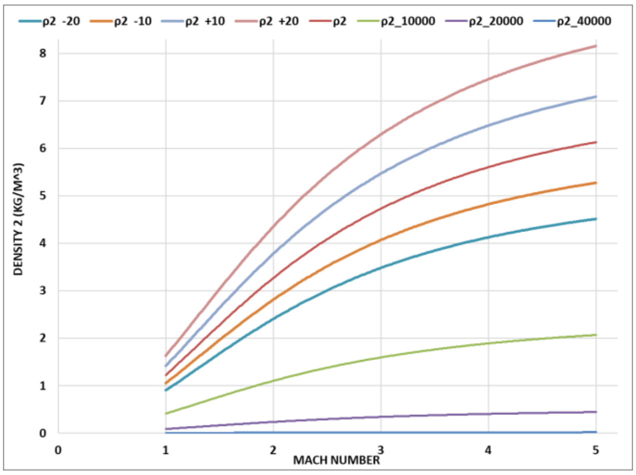

Fig. 9. Mach, Post-Shock Density Graph for Configurations 1 and 2

3.2 Conclusion and Recommendations

As can be understood from all these findings, it was determined that ignoring the atmospheric conditions led to data that did not match the actual values found in the current conditions. This is expected to cause problems in the design and analysis processes. For this design and analysis process, compressible flow parameters are of critical importance for performance-based design of engines and compressors [35], air intake and wing designs [36,37], in short, in all cases that directly affect the aerodynamic and structural design of the aircraft [38]. This is because flow regimes and aerodynamic forces can change depending on the compressibility effects of the flow [38]. While the variation of the stress acting on the aircraft affects the material selection [39], the varying thermal loads also create a material selection based on the resistance of the aircraft to thermal stresses. Total temperature information is critical for the calculation of thermal expansion and deformation [40]. This study can be integrated into computational fluid dynamics (CFD)-based software to enable more comprehensive analyses and serve as a foundation for future research.

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