



LAXMI CHARITABLE TRUST

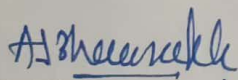
SHRI CHINAI COLLEGE OF COMMERCE & ECONOMICS

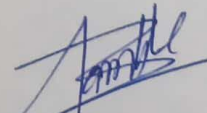
Dr. S. Radhakrishnan Marg, Andheri(East), Mumbai-400069

Accredited by NAAC with B Grade

3.3.1 Number of research papers published per teacher in the Journals notified on UGC CARE list during the last five years

Sr. No.	Name of the Teacher	Title of paper	Year
1	Asst.Prof. Manish Jaiswal	Ai Power Gaming and Cultural Fusion: Transformative Gaming Experience on Indian-Centric GTA V Servers	2023-2024
		A Review of Covid-19'S Impact on Agricultural Economy	
2	Asst.Prof. Chetan Panchal	An Empirical study on impact of COVID - 19 on investment pattern of the investor with reference to Mumbai Region	2021-2022
3	Asst.Prof. Manish Jaiswal	The diurnal variation characteristics latent heat flux under different underlying surfaces and analysis of its drivers	2022-2023


IQAC Coordinator


I/C PRINCIPAL



AI-Powered Gaming And Cultural Fusion: Transformative Gaming Experiences On Indian-Centric GTA V Servers

Ameya Prashant Yadav^{1*}, Vaishnavi Jadhav², Abhishek Dipak Shroff³, Pradip Salve⁴, Harshal Patil⁵, Prof. Manishkumar Jaiswal⁶

^{1,2}B-Tech Artificial Intelligence, School of Engineering, Ajeenkya DY Patil University, Pune Maharashtra, India

^{3,4}Assistant Professor, School of Engineering, Ajeenkya DY Patil University, Pune Maharashtra, India.

⁵Assistant Professor, RCPIT, Shirpur, India.

⁶Assistant Professor, Shri Chinai College of Commerce & Economics, Mumbai, Maharashtra, India.

Citation: Ameya Prashant Yadav, et al (2024), AI-Powered Gaming and Cultural Fusion: Transformative Gaming Experiences on Indian-Centric GTA V Servers, *Educational Administration: Theory and Practice*, 30(5), 6621-6627. Doi: 10.53555/kuey.v30i5.3991

ARTICLE INFO

ABSTRACT

This research delves into the multifaceted realm of AI-driven GTA V Five M role-playing gaming servers, focusing on the integration of Indian culture, technical challenges, and security measures. Grand Theft Auto V (GTA 5) serves as the backdrop, offering an expansive open-world setting where players engage in quests and multiplayer experiences on customized dedicated servers. Our investigation combines player behavior analysis with an exploration of the technical intricacies involved in developing, testing, and deploying these servers. The study reveals diverse player behaviors, including socializing, competing, and role-playing, alongside technological challenges such as server performance, security concerns, and cheating. Through detailed methodologies, risk analyses, and developmental stages, the research aims to enhance both player enjoyment and the overall security posture of AI-driven GTA V gaming servers. The integration of Indian culture further distinguishes these servers, fostering a unique and immersive gaming experience that resonates with players on a cultural level. The findings contribute valuable insights for the ongoing evolution of online gaming environments, emphasizing the significance of both technical proficiency and cultural integration.

Keywords: AI-driven Gaming, Role-Playing Servers, Security Measures, Player Behavior Analysis, Technical Challenges, Cultural Integration.

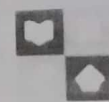
I. INTRODUCTION

This research embarks on an in-depth exploration of AI-driven GTA V Five M role-playing gaming servers with a primary focus on the amalgamation of Indian culture, addressing technical challenges, and implementing robust security measures. In the expansive realm of Grand Theft Auto V (GTA 5), players partake in immersive multiplayer experiences within custom-designed virtual landscapes. This paper endeavors to dissect and comprehend player behavior intricacies, intricacies involved in server development, and the pivotal role of cultural integration in crafting a distinctive gaming milieu. As online gaming continually evolves, comprehending the nuances of technical challenges and the infusion of cultural elements becomes imperative for fortifying security measures and elevating the overall satisfaction of players within these virtual communities.

As the gaming ecosystem continues to evolve, this paper endeavors to dissect the nuanced complexities of player behavior, delve into the intricacies of server development, and underscore the pivotal role of cultural integration in crafting a gaming milieu that is both unique and culturally resonant. Our journey encompasses not only the technical challenges faced in the development

In the dynamic landscape of contemporary gaming, this research embarks on an extensive exploration of AI-driven GTA V Five M role-playing gaming servers. Our primary focus lies in unraveling the intricate layers of these servers, accentuating the integration of Indian culture, grappling with technical challenges, and implementing robust security measures. Grand Theft Auto V (GTA 5) provides a multifaceted canvas, offering players an immersive multiplayer experience within carefully tailored virtual landscapes.

Understanding player behavior within these servers, with its diverse facets of socialization, competition, and role-playing, is paramount for the continual improvement of gaming experiences. Simultaneously, delving



A Review Of Covid-19's Impact On Agriculture Economy

Dr. Rajendra Bapurao Vhatkar^{1*}, Dr. Vishwajeet S. Goswami², Abhishek Dipak Shroff³, Pradip Salve⁴, Prof. Manishkumar Jaiswal⁵, Puja Saraf⁶,

^{1*}Asst Professor, Dept. of Mathematics, S.N College of Arts & Commerce, Thane, Maharashtra.

^{2,3,4}Assistant Professor, School of Engineering, Ajeenkya DY Patil University, Pune Maharashtra, India.

⁵Assistant Professor, Department of Mathematics, Shri Chinai College of Commerce & Economics, Mumbai, Maharashtra.

⁶Assistant Professor, Computer Engineering, RCPIT, Shirpur, India.

Citation: Dr. Rajendra Bapurao Vhatkar, et al (2024), A Review Of Covid-19's Impact On Agriculture Economy. *Educational Administration: Theory and Practice*, 30(5), 6613 to 6620, Doi: 10.53555/kuey.v30i5.3989

ARTICLE INFO

ABSTRACT

The global economy has been severely disrupted by the growth and spread of the COVID-19 coronavirus outbreak, which has caused imbalances in all areas of society worldwide. Social distance, quarantine laws, and stringent travel restrictions have resulted in a significant decline in the labor force and employment losses in every industrial sector. The food and agriculture sectors were the most vulnerable and impacted. The government's decision to declare a national civil lockdown caused businesses all across the world to close, which had an effect on the flow of goods from farmers to consumers. Presenting workable solutions that may simultaneously boost the market and satisfy customers—even in the midst of a severe pandemic—is urgently needed. This study examines how COVID-19 has affected the agro-food system and its economics, highlighting important elements such as labor availability, food security, interconnectedness of the farming system, and resilience of the agricultural sector. A robust and independent society may be developed by potential innovations including technological adoption, risk detection and management, government action, and policy changes.

Keywords: Agriculture, COVID-19, Food security, Agricultural system resilience, Pandemic, Management.

1. INTRODUCTION

The global coronavirus (COVID-19) epidemic presented a serious risk to public health and had an impact on many areas of human existence. Food insecurity resulted from the virus's quick spread and impact on economies, which led to inefficiencies in the industrial and agricultural sectors. Numerous national and international institutions, such as the International Food Policy Research Institute (IFPRI) and the Food and Agricultural Organization (FAO), have long supported the economies of many different countries through agriculture. ... Significant changes occurred in the agriculture sector in the late 1900s, as Fig. 1 illustrates, moving from labor-intensive, bullock farming to mechanized and the use of larger tools in the twenty-first century. In addition to contemporary machinery, advancements in crop types, digital supply chain solutions, and the application of various agri-inputs were additional factors aimed at boosting productivity and yield. This gave rise to a revolution in the agro-food industry. Since the abrupt COVID-19 breakout, the agro-business has been expected to be the main driver of growth for managing international trade relations and balancing import-export.

The first indications of the virus appeared in December 2019 when a pneumonia outbreak occurred in China's Wuhan province. In January 2020, the World Health Organization (WHO) subsequently deemed the COVID-19 outbreak to be a public health emergency of global significance. Globally, the virus's constant spread has resulted in a 3.4% crude fatality rate. After starting in China, the COVID-19 pandemic gradually expanded to 190 other nations. India rose to prominence as one of the COVID-19 epicenters around September 2020. Because of the daily increase in instances, the National Institute of Epidemiology and Bloomberg report suggest that the nation may easily overtake the United States and Brazil. In this interconnected society, prevention has been shown to be a difficult road by the hidden cascading domino effect, but management is still possible, even in dire circumstances like the COVID-19 pandemic. The food and agriculture industries are

“AN EMPIRICAL STUDY ON IMPACT OF COVID – 19 ON INVESTMENT PATTERN OF THE INVESTOR WITH REFERENCE TO MUMBAI REGION”

B.B. Kamble¹ and C. Panchal²

^{1,2}Shri Chinai College of Commerce & Economics, Andheri (E) Mumbai
¹bbkamble73@gmail.com, ²chetanpanchal188@gmail.com

ABSTRACT

COVID- 19 or Novel Corona virus has adversely affected worldwide. The COVID - 19 pandemic has not only introduces new health issues but also enhances health crisis and has changed individual's financial conditions, which adversely influenced on individual's saving and investment pattern. To have control over the pandemic situation, government has taken certain corrective measures such as lockdown, wearing the mask, and social distancing etc. Because of such kind of restrictions on free movement of economic activity the entire economy got blocked and people or individuals losses their jobs. It automatically leads to reduction in income of the people, which has drastically affected on two main important economic pillars of the economy i.e saving and investment. The study is undertaken to understand how the COVID – 19 pandemic has impacted investment pattern of investors especially in Mumbai region because Mumbai is a metropolitan city and economic capital of the country. To know and understand investment pattern during COVID 19 a survey has been conducted with random sampling of 50 investors in Mumbai region. The investigation has done with different review of literature in Investment areas, all primary random sample data collected from Mumbai region and using parametric and non – parametric statistical methods, and secondary data collected from different journals, books and government records. The findings of the study will helpful to identify the investor's preference during COVID – 19 pandemic situation and also understand their investment pattern

Key Word: COVID -19, Investment Pattern, Saving, Lockdown

Introduction:

On February 11, 2020 World Health Organisation officially declared COVID 19 or Novel coronavirus is a deadly virus. On 11th March 2020 the World Health Organization (WHO) declared COVID -19 a global pandemic. It also confirmed that a COVID -19 or Novel coronavirus was the cause of a respiratory illness in a cluster of people in Wuhan, China.

In India first case of COVID -19 was confirmed on 30 January 2020 in Thrissur, Kerala, Which was infected by many peoples. To manage such severely emerging condition, on 25th march 2020, the government of India declared a three week country wide lockdown. During this period, all educational institutions, private offices, public and tourist places, public utility, non-essential activities, religious places etc. were shut down.

To control infectious of COVID -19 the government took some corrective measures such as lockdown, wearing the mask, and social distancing etc. Because of the lockdown Majority economic activities got blocked and unemployment drastically increases, people's saving reduced and has adversely affected on people's standard of living, and investment pattern.

Mumbai is a densely populated city in India and is financial capital of the country besides that most of the company's headquarters are located in and around plus important stock exchange like Bombay Stock Exchange is existing in the city. Therefore millions of people migrated in search of employment. But due to pandemic situation people became unemployed during the lockdown and they left the Mumbai city. The main reason of leaving the city was unemployment this adversely influence on people's investment pattern.

Though the Mumbai is financial capital of the country and having good atmosphere to invest yet due to COVID-19's situation people doesn't have that capacity to invest however in a given situation with available resources whenever they invest that time they do consider the following points

Factors Influencing or affecting investment pattern of investors are as follows

Return on Investment: The main purpose of investor is to earn sufficient return on investment. Therefore investors always analyse investment avenues that which avenues gives more rate of return on investment and accordingly allocate their resources in optimum manner.

Inflation: Inflation is one of the important factor for investment because every investor wants to beat the inflation rate and want reap good earning in future. He will receive positive return only after analysing inflation rate consideration and if it is less than the return on the investment.

Liquidity: In any prudent investment decision liquidity plays very significant role. Because market provide many opportunities so investors wants to exploit and should have enough scope to liquid at appropriate time.

Risk in Investment: generally risk is an anticipated parameter with which one can calculate the earnings on investment. If it's more the returns will be more and vice versa. Therefore every investor always concedes the risk involved in investment. Those investors who take more risk invest in a high risky avenues and low risk investors try to invest in a low risk investment avenues.

Safety in Investment: Safety is the most significant factors in investment decision. It will be conceded by those investors who are not ready to take any kind of risk and they wanted to how safety in investment. Generally fixed rate of returns investment avenues will be considered by the Investors. No doubt the returns are comparatively low in this case.

Review of Literature

Arpita Gurbaxani, Rajani Gupte 2021 in this paper entitled A Study on the impact of COVID - 19 on investor Behaviour of individuals in a Small Town in the State of Madhya Pradesh, India observe that the outbreak of COVID -19 infectious virus adversely affected human life. For prevention of deadly virus government took some corrective measures like lockdown. Due to lockdown economic activity slowdown further they also compared COVID -19 outbreak with financial crisis of 2008, based on some literature review. They also analysed the different factors influencing in investment decision such as demographic factor affecting mutual fund investment decisions, Factors influencing individual investors behaviour, Individual investor perception during the financial crisis, Impact of COVID -19 on household income and impact of COVID -19 on financial market. Author use 100

respondents in tier 3 town in Madhya Pradesh to analysis investor to prefer investment in different channel like mutual fund and stock market area and also tested the hypothesis. They conclude that due COVID -19 outbreak has significantly impact the economy especially in financial sector. There is negative impact seen especially retail investors and investors are diversify their portfolio they select safe investment pattern like gold ETF.

Dr. S. Saravanan¹, Dr. S. N. Sukumar², Ms. Suvarna Raagavendaran³, Ms. T. Shammy⁴ 2021 in this study Impact of Covid-19 on Foreign Direct Investment in India observe that India is the second main destination of investment after china. Government of India and reserve bank of India taking some corrective measure to enhance the foreign investment activity. Author also measure relationship between foreign direct investment and economic growth and also analyse FDI approval and actual inflow, sector wise and state wise FDI inflow. The finding of the investigation that foreign direct investment has not been build up as a huge deciding element for the monetary development of India. Country should develop more attractive norms to enhance FDI in different sectors.

Monika Chaudhary¹, P. R. Sodani¹ and Shankar Das² 2020 studied that Effect of COVID-19 on Economy in India: Some Reflections for Policy and Programme in this study author examine impact of COVID - 19 in different sector. Further they investigate that due to unprecedented situation has caused a great damage to the economy especially aviation industry, tourism industry, retail industry, capital market and MSMEs sector. The finding of the research that every crisis provide unique opportunity to rethink on the path for development of a human being, and society. This unprecedented crisis gave clear message for the Indian economy to adopt sustainable development models, which are based on self - reliance, inclusive frameworks and are environment friendly .By going through the above literatures be found that during the respective ear whatever crisis where arisen that time the economy has a different setback and in tune of that the corrective measures were taken to reforms or redesign the economy. But in this particular crises the

industry does not have any scope to rebuilt or redevelop as lockdown has taken away the opportunity. So this was definitely some think different compare to the earlier crises.

Scope of the Study

This study would be undertaken to analyse the Impact of COVID – 19 on investment pattern of the investor.it would also helpful to us to understand the situation during such financial crisis and accordingly investors can take investment decision. Thus present study's main aims is to analysed impact of COVID -19 and how it influences on investment pattern of investors especially in Mumbai region.

Research Methodology

It's a specific procedure adopted by the researcher to identify, select, process or analysed the information used in the research paper. It also helps to the researcher to evaluate overall reliability and validity of the research paper.in short the systematic way or method of doing the research it's called research methodology. Here the researcher has adopted following methods.

Problems of the study: the study is on the impact of COVID 19 on investment pattern of investors and what are the problems face by the investors in this unprecedented situation.

Research objective:

- 1) To study the investment pattern before COVID then
- 2) To study the pattern of investment during the COVID
- 3) To understand different investment opportunity during COVID -19

Hypotheses

In Light of the discussion in preceding sections, the following hypotheses are proposed:

H0: There is no significance in amount of investment before and during the COVID 19 outbreak

H1: There is significance in amount of invested in equity market before and during the COVID 19 outbreak

Research Design

The research design guidelines about the data element. The study is based on both primary data and secondary data. The primary data was collected through structured questionnaire for which samples of 50 respondents (Investors) were selected from different areas of the city. . The collected samples using convenient sampling method are validated and taken it for further analysis. Secondary data is also collected and used from different database sites, journals and articles. The collected data is analysed with parametric and non-parametric statistical methods.

Area of the Study

The study is undertaken in and around the Mumbai city and its suburban areas.

Research Approach

The questionnaire methods survey is used for collecting primary data from investors in Mumbai region. We requested all respondents to fill in the questionnaire, by self-explaining the various aspects mentioned in it. It contained both open and closed ended questions in the structured form which are very easy to understand at a glance.

Sample Technique

IA convenient sample (Probability sampling method) of 50 investors in Mumbai region was shared their information to the study was request to complete the questionnaire on voluntary basis. The study was done in August and September 2021

Data usage

The analyses and interpretation is done on the basis of primary data. However for conclusion and recommendation both primary and secondary data is used along with the verbal knowledge and information obtained from respondents. The outside parameters which are out of questionnaires are also considered. The data collected from these source were analysed using various tools like correlation and t -test methods

Table – 1 : Age, Gender, occupation and Income wise Demographic Pattern of individual investors

Demographic Category of investor	Parameters	Number of Representatives	
		Total (50)	Percentage
Gender	Male	28	56%
	Female	22	44%
Age	up to 25 years	18	36%
	26 to 35 years	12	24%
	36 to 45 years	10	20%
	46 to 60 years	7	14%
	61 years and above	3	6%
Occupations (Employment)	Self-employed Professional	31	62%
	Entrepreneurs	5	10%
	Salaried employees	14	28%
Annual Income	Up to 3 Lakhs P.A	30	60%
	Rs. 3 Lakhs to 5 Lakhs P.A.	10	20%
	Rs 6 Lakhs to 8 Lakhs P.A	6	12%
	More than 8 Lakhs P.A	4	8%

**Table. 2
Showing the ranks given by investors on various investment options**

Investment options	Investment Percentage	Rank
1. Equity Shares	23%	1st Rank
2. Fixed Deposits	21%	2nd Rank
3. Mutual funds / ULIP / ELSS	15%	3rd Rank
4. LIC Policies	10%	4th Rank
5. Postal savings schemes	8%	5th Rank
6. Public Provident fund / EPF / Pension schemes	7%	6th Rank
7. Bullion (gold, silver, ornaments)	6%	7th Rank
8. Bonds / Debentures	5%	8th Rank
9. Real Estate	4%	9th Rank
10. Others	1%	10th Rank

The above table shows that around 23% of population invests in equity market and they prefer to have moderate risk in investment with high returns. Therefore they secured 1st rank and around 21% population invested in secured investment with good returns and they secured 2nd rank in our research category. Rank 3rd secured by Mutual funds / ULIP / ELSS and Rank 4th LIC Policies. In our investigation we

found that around 8% of population invest in Postal savings schemes and they secured Rank 5th and Rank 6th manage by Public Provident fund / EPF / Pension schemes. Rank 7th fixed by Bullion (gold, silver, ornaments) and around 5% population invested bond and debenture and obtain Rank 8th, Rank 9th and Rank 10th manage by Real estate and other investment

Table Number. 3: Hypothesis testing

t-Test: Two-Sample Assuming Unequal Variances		
	Before COVID investment	During COVID investment
Mean	20530	12898
Variance	457596020.4	203710404.1
Observations	50	50
Hypothesized Mean Difference	0	
Df	85	
t Stat	2.09856291	
P(T<=t) one-tail	0.019411494	
t Critical one-tail	1.6629785	
P(T<=t) two-tail	0.038822989	
t Critical two-tail	1.988267907	

The p value for investment before and during the COVID 19 outbreak were less than 0.05 there for our null hypothesis rejected and alternative hypothesis accepted. It may be said that there is significance in amount of invested in equity market before and during the COVID 19 outbreak

Conclusion: The COVID 19 outbreak has significantly impacted in financial sectors. Due

to control COVID 19 infection government took some corrective measures like lockdown, wearing mask and maintain social distance. Due to this corrective measures economy move set back and their adverse side effects seen such as stock market crash, individual reduces their return on investment. In the study we found the major impact our investment pattern of the investor during COVID 19.

References

1. Chakraborty, I & Maity, P, 2020, 'COVID - 19 outbreak: Migration, effects on society, global environment and prevention', *Science of the Total Environment*, 138882.
2. Dev, SM & Sengupta R, 2020, COVID-19: Impact on the Indian economy', *Indira Gandhi Institute of Development Research, Mumbai April*
3. Garde, S, Bhadada P & Gupta, M, 2020, April 28, 'Indian SMBs – On Road To Recovery From COVID -19',
4. Krishnudu C, Reddy, BK & Reddy, GR, 2009, 'Investment Behaviour and Risk Management', *Global Research Publication*
5. Arpita Gurbaxani, Rajani Gupte 2021 'A Study on the impact of COVID - 19 on investor Behaviour of individuals in a Small Town in the State of Madhya Pradesh, India'
6. Dr. S. Saravanan¹, Dr. S. N. Sukumar², Ms. Suvarna Raagavendaran³, Ms. T. Shammy⁴ 2021 'Impact of Covid-19 on Foreign Direct Investment in India'
7. Monika Chaudhary¹, P. R. Sodanil and Shankar Das² 2020 'Effect of COVID-19 on Economy in India: Some Reflections for Policy and Programme'
8. Borensztein, E., De Gregorio, J and Jee, J.W (1998) How Does foreign Direct Investment Affect Growth? *Journal of International Economics*, Vol.45, pp.115-135
9. Ducharme, J (2020) World Health Organization Declares COVID-19 a 'Pandemic.' Here's What That Means. *Time Online Newspaper*, Retrieved April 20, 2020, from [https://time.com/5791661/who-coronavirus-pandemic-declaration/March.11.Foster.L.\(2012\).Does.the.US.Presidential.Election.Impact.the.Stock.Market?CFA.Institute.Web](https://time.com/5791661/who-coronavirus-pandemic-declaration/March.11.Foster.L.(2012).Does.the.US.Presidential.Election.Impact.the.Stock.Market?CFA.Institute.Web).
10. Tomar, A & Gupta, N, 2020, 'Prediction for the spread of COVID-19 in India and effectiveness of preventive measures', *Science of The Total Environment*, 138762.
11. Ram, A, 2020, April 21, COVID -19 Impact on stock market', *outlook money*.

The Diurnal Variation Characteristics of Latent Heat Flux under Different Underlying Surfaces and Analysis of Its Drivers

Dr. Rajendra Bapurao Vhatkar¹, Dr. Vishwajeet S.Goswami², Prof. Manishkumar Jaiswal³

¹Asst Professor, Dept. of Mathematics, S.N College of Arts & Commerce, Thane, Maharashtra.

²Asst. Professor, Dept. of Mathematics, UIS. Chandigarh University

³Assistant Professor, Department of Mathematics, Shri Chinai College of Commerce & Economics, Mumbai, Maharashtra.

Abstract : Monitoring the Latent Heat Flow is crucial for managing water resources and determining the crop water demand because it is a crucial part of the hydrological cycle and surface water heat transfer. The Heihe River Basin's distinctive topography guarantees improved variable control in LE analysis. In this work, the time series analysis and statistics of LE under various underlying surface conditions in the summer were carried out, and the regression components were looked at, using the eddy correlation observation data from the Heihe River Basin. The results show that when the underlying surface types are significantly different, there are discernible differences in the daily distribution of LE, the daily fluctuation trend of LE, and the influencing factors. The range of LE's diurnal distribution in the desert, Gobi, and dunes is 50 to 100 W/m². Vegetable fields, cornfields, and marshes had a diurnal LE distribution that was roughly 55% concentrated between 50 and 100 W/m². The two main elements influencing latent heat flux are temperature and carbon dioxide content (CO₂). Stepwise regression analysis is used to further analyse temperature and CO₂ levels, and numerous regression models are created. In terms of correlation and confidence, the outcomes outperform single factor fitting and are better able to reflect the interplay between temperature and CO₂ on LE.

Keywords :- Eddy correlation, latent heat flux, the underlying surface, the weather, and an area with sparse vegetation

1. Introduction

Latent heat flux, which is evapotranspiration's energy expression, plays a key role in the hydrologic cycle, hydrologic prediction, and activities involving the transfer of heat from surface water. [1–5]

Latent heat of evapotranspiration is one of the key mechanisms controlling the energy and water exchange between the hydrosphere, atmosphere, and biosphere [6,7]. It is a crucial component of the hydrological cycle because it reflects the environment's highest water demand and helps to keep the water balance [8,9]. Evapotranspiration reflects the water needs of crops, however it is challenging to quantify evapotranspiration precisely. The LE can better depict evapotranspiration. From a meteorological and environmental perspective, the climate and environmental factors that affect LE typically include net radiation, relative humidity, air temperature, and leaf area index.

Numerous academics and researchers have studied and analysed the response relationship between LE and its drivers on the space-time scale, but the results are not always consistent, particularly when categorising the sensitivity of meteorological parameters [10–12]. It suggests that there is some one-sidedness in the way temperature, environment, and other variables are controlled when examining the interaction between drivers and LE in terms of responsiveness. The analysis results from past study were usually spatially dependent and difficult to build a sound inquiry since there was typically only one underlying surface or a large spatial difference between many underlying surfaces. The estimation and measurement methods for LE have long been a hot topic among academics. Numerous methods are used to assess evapotranspiration, including the owen ratio energy balance approach, remote sensing, in situ measurement, hydrologic, and eddy correlation methods [13–19]. Under challenging geomorphological circumstances, the accuracy of the Bowen ratio-energy balance method is constrained. The hydrology approach, which is founded on the concept of water balance, is used to calculate the total evapotranspiration in the study area. The method has drawbacks, such as a long temporal scale (water balance approach) or a brief spatial scale (vaporation method) [20,21]. Although remote sensing can be used for extensive long-term observations, it cannot be continuous because of the short transit time and limited operating cycle of satellites. The circumstances that apply, the theoretical underpinnings, and the measuring range of various approaches vary. Eddy correlation can quickly gather a lot of data on evapotranspiration and environmental change since fewer theoretical presumptions, high precision, rapid measurement, and great temporal resolution are some of its benefits. [22]. The technique offers a direct confirmation for the currently used soil-

vegetation-atmosphere material-energy exchange model. The "Joint Experiment on Integrated Remote Sensing Observation of Eco-Hydrological Processes in the Heihe River Basin" (EC) system, which was developed [23], is used in the study. Variable control is ensured throughout LE analysis thanks to the Heihe River Basin's diverse landscape, which includes sand dunes, the Gobi Desert, vegetable and maize crops, and deserts. The middle reaches of the Heihe River's typical desert oasis landform are the subject of this study and is based on the EC system observation data of the "Integrated Remote Sensing Observation Joint Experiment of Eco-Hydrological Processes in the Heihe River Basin" [14] and based on factors including correlation analysis, LE daily variation curve, and LE daily frequency distribution, among others. The properties of latent heat flux and the response relationship of its influencing components are explored while taking into account spatiotemporal variation and land cover type.

2. Substantials and Acting Methods

Research Area of Study

The research area is located in Zhangye City, Gansu Province, which is the central oasis in the middle reaches of the Heihe River Basin (HRB) (100.104-100.853 E, 38.549-39.399 N). With an average height of 1474 metres, the middle temperate zone has semi-arid and arid weather. In July, the average monthly high temperature is 29.3 degrees Celsius, while January has an average monthly low temperature of 16.2 degrees Celsius. July has 9.4 days of average monthly precipitation, 130.44 mm of average annual precipitation, and 51.6 days of average annual precipitation. With an average yearly evaporation of 2000–3500 mm and a large difference in temperature between day and night, the region sees significant evaporation.

Six stations were chosen for this article. In Zhangye city, Gansu province's Daman irrigation district, is where you'll find the Daman superstation. While the undersides of encryption stations 1 and 12 are both vegetable fields and cornfields, respectively, the Huazhaizi station has a typical desert subsurface with sparse red and pearl sand sprouting on the surface. Due to the Bajitan station's primary coarse sand and gravel surface, a lack of water, and a paucity of plants, only a few drought-tolerant species, like tamarisk and camel thorn, may grow there. The Shenshawo station is a desert area mostly covered in sand with unusual plants and dry air, in contrast to the Wetland station where the underlying surface is a wetland with adequate wetness and rich

vegetation. The Heihe Hydrological Remote Sensing Experiment's subsite stations of the Daman Super Station are fields of vegetables and maize, where the information for these stations was gathered. These websites are thorough, educational, and excellent for research. The precise statistics and site distribution in the study area are shown in Table 1 and Figure 1. The land cover of the Heihe River Basin is shown in Figure 2 [24].

Table 1. Site name and study topic-related details

Name of Site	Underlay Surface name	Altitude	Data in and out time
station 1	Vegetable ground	1552.8 5	June–31 August
station 12	Cornfield	1559.3 1	June–31 August 31
Shenshawo station	Dune	1562.6	1 June–31 August (data unavailable on August
jitan station	Gobi	1731.0	2)
	Desert	1549.4 2	7 June – 31 August
Huazhaizi station	Wetland	1460.0	June–30 August
Wetland station			26 June to 30 August

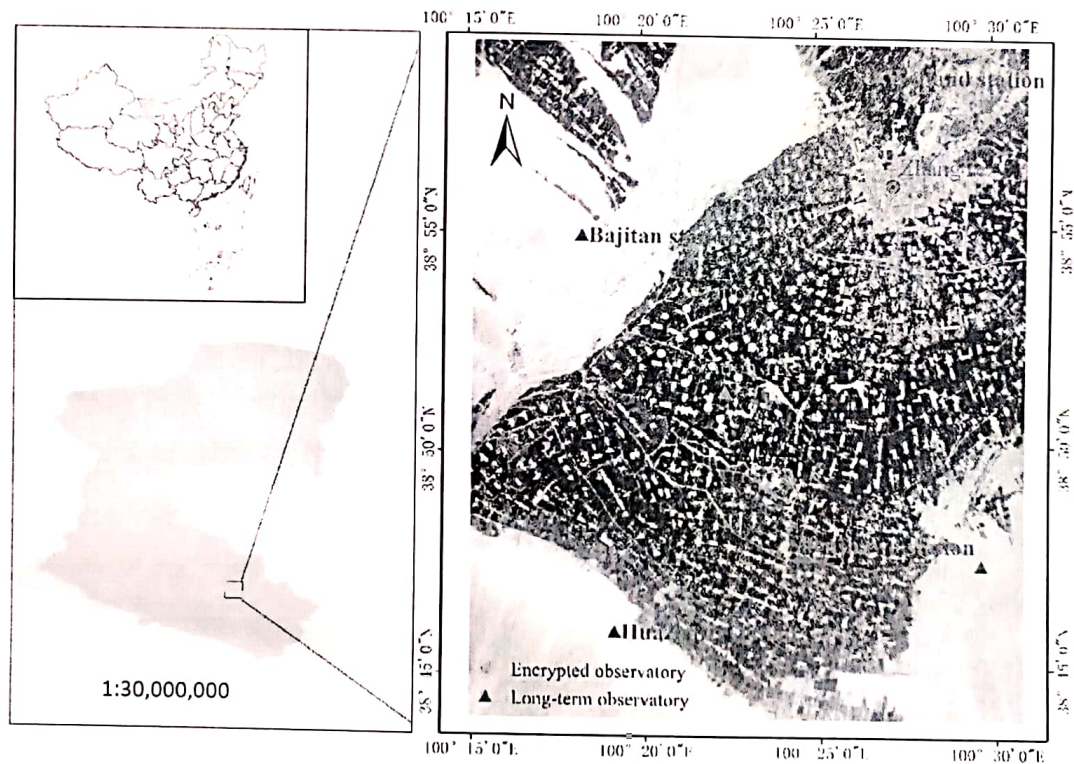


Figure 1. Map of the research area's locations and site dispersal.

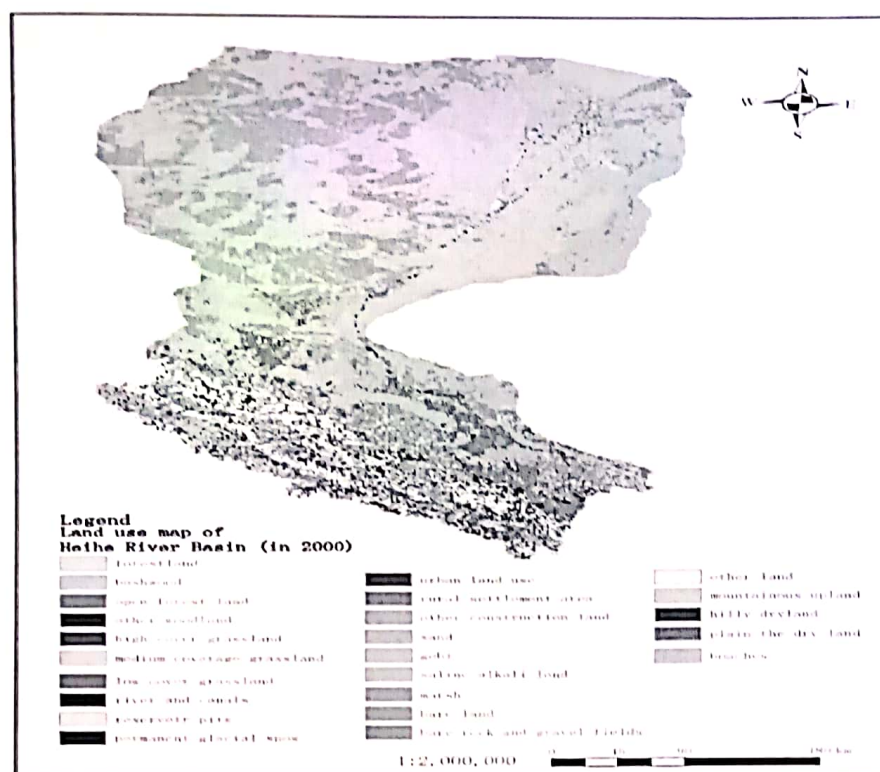


Figure 2. Heihe River Basin land cover map.

2.2. Tool and Trial Content

An image spectrometer, a charge-coupled device (CCD), a light detection and ranging (lidar) system, a multi-angle thermal infrared camera, a microwave radiometer, and a light detection and range system were all employed in the experiment. The standard automatic meteorological station (AMS) measures the soil heat flux, soil moisture and temperature profiles, air pressure, wind direction and speed, air temperature, and radiation throughout the entire HRB. The superstation was outfitted with an EC system, a Bowen ration energy balancing device, a LAS (long aperture scintillometer), and a lysimeter to monitor fluxes at various scales. The land surface temperature (LST), photosynthetically active radiation (PAR), and standard station data are all also measured by superstations. The instrument is thoroughly introduced in Li's paper [25,26].

2.3. Research Data

The data required for this paper come from the "Joint Telemetry Experimental Study in the Heihe River Basin," also known as "HiWATER [23,26,27], this combines an experiment with the observation of ecohydrological processes using remote sensing in the Heihe River Basin. In addition to two encrypted stations 1 and 12 in the Daman irrigation region (a vegetable field and a cornfield, respectively), the following will make use of the Gobi, desert, dune, and wetland stations. Bajitan, Huazhaizi, Shenshawo, wetland station in the middle reaches of the Heihe River, and wetland station made up the total of six stations chosen for this investigation. The horizontal wind velocity, air temperature, water vapour density, carbon dioxide concentration, and latent heat flux EC observation data were selected and obtained via the Heihe Plan Data Management Centre Network (<http://westdc.westgis.ac.cn>, accessed on: 1 September 2022). Although there were gaps in the data for the weeks prior to June 25 at the wetland station and August 2 at the Bajitan Station, the data interval on average was 30 minutes. The start and end times of the study area locations and data are shown in Table 1.

2.4. Data Process

The EC observations have a minor number of missing values. The early and late time periods are where the majority of the missing portion is located and the interpolation data is mostly LE. The analysis is unaffected by the lack of a clear LE trend over these two time periods. The addition of linear interpolation to the data. Stepwise regression analyses presented screening findings in descending order and took taking the involvement of independent factors into consideration. Since model identification merely needs optimising the coefficients of each input, it is frequently used [28]. The AIC (Akaike information criterion) criterion is then applied to achieve automatic parameter optimisation.

Stepwise regression techniques and correlation coefficients (R) must be utilised to analyse LE and its drivers in this work. The introductions that follow are connected: The R has been commonly employed to quantify the average disparity between models, despite the fact that they are oversensitive to high extreme values (outliers) [29,30].

R will be defined as

$$R = \frac{n \sum_{i=1}^n (Q_0(i) - Q_0)(Q_f(i) - Q_f) s}{\text{Sq}(n \sum_{i=1}^n (Q_0(i) - Q_0)^2) * \text{Sq}(n \sum_{i=1}^n (Q_f(i) - Q_f)^2)}$$

The information-theoretic approaches provide the foundation of Akaike's information criterion (AIC) [31]. It serves as a benchmark for judging the accuracy of statistical model fitting and the complexity of statistical models. The complexity of the model tends to rise as the amount of data used in model training increases. At the same time, it is challenging to prevent overfitting issues. Methods like AIC and BIC (Bayesian Information Criterion) are frequently used to prevent over-fitting of the model. Given a large sample size, the BIC method yields a more desirable result because its penalty term is larger than that of the AIC method [32]. To prevent overfitting, we should prioritise models with the lowest AIC values when using AIC to assess model fit [33]. Generally A/C expressed as

$$AIC = 2k - 2 \ln(L) \quad \dots\dots\dots (a)$$

L is the likelihood function, and k is the number of parameters.

The error of the model is subject to a separate normal distribution:

$$AIC = 2k + n \ln(RSS/n) \quad \dots\dots\dots(b)$$

where n is the number of observations, and RSS (Residual Sum of Squares) denotes the total of the residuals.

Multiple regression analysis usually involves a large number of effect factors, therefore computing the full set of parameters can be highly expensive [34].

Stepwise regression is a trustworthy method [35]

Following the quadratic response surface model, the stepwise regression model is shown as

$$y(x) = a_0 + \sum_{i=1}^n a_i x_i + \sum_{i=1}^n a_{ii} x_i^2 + \sum_{j < i}^n a_{jix} x_j x_i$$

The stepwise regression approach adds the significant independent variables into the regression equation in the order of the independent variables in the model.

Reexamining the significance level test at the predetermined F or AIC level and removing variables that are not significantly impacted by the dependent variable until the variables are unable to improve the model by reintroducing the independent variables results in the completion of the regression process and the best regression equation [34,35]. Equation (4) states that factor interactions as well as linear or nonlinear correlations among factors may be the subjects of stepwise regression. A flowchart of the calculations is shown in Figure 3.

3. Results

3.1. Analysis of the Trend in LE Variation for Various Underlying Surface Types

Using LE data from the months of June, July, and August of 2012, a time series visual based on numerous underlying surface types was produced.

Figure 3 demonstrates that LE has a comparable pattern over time and that the current underlying surface conditions (soil moisture content and vegetation coverage) are comparable. These elements suggest that the current underlying surface conditions are likely to persist when combined with the weather data for Zhangye city in June, July, and August 2012. Additional information on the LE trend line's fluctuation is obtained, which is roughly consistent with changes in the weather from sunny to rainy.

In order to further evaluate the characteristics and distribution rules of LE days with sunny days used as a control variable, station data (vertical line markers) with weather conditions as sunny days for three months were selected.

Using sunny days as a control condition and based on several sites, we selected the 9-day LE data for the dates of 8 June, 19 June, 29 June, 9 July, 13 July, 31 July, 2 August, 21 August, and 27 August 2012. The nine days of the LE intraday frequency distribution histogram were then mapped. Additionally offered are statistics for LE days. As demonstrated in Figure 4 and Table 2, each site's peak value and standard deviation are notably different, and this variation is directly related to the type of underlying surface. The LE maximum for vegetated land was 661.3 W/m², whereas the LE minimum for dunes was 201.2 W/m². The LE standard deviation for cornfield is 180.8 W/m², while the LE standard deviation for dunes is 39.3 W/m². While the distribution of LE values in the Gobi, sand, and desert is largely dispersed and gradual, it is relatively concentrated and steep in vegetable fields, cornfields, and wetland.

The kurtosis can show how steeply and slowly the pattern is spread, and the standard deviation can show how dispersed the study object is.

The cumulative values for the Gobi, dune, and desert on the 50-100 W/m² interval are 92.4%, 89.5%, and 94.1%, respectively. The cumulative values for the vegetable land, corn land, and wetland on the 50-100 W/m² interval are 53.8%, 54%, and 57.7%, respectively.

Even though the underlying surface features of each site differ, a careful analysis of the aforementioned data allows us to approximately divide each site into two groups: dry (Gobi, dune, desert) and moist (vegetable, maize, and wetland). The LE value of the underlying surface is concentrated between 50 and 100 W/m² in a dry atmosphere.

Under the moist circumstances of the underlying surface, the LE value is concentrated between 50 and 100 W/m², but with a significant degree of dispersion; 42.2 to 46.2% of the LE value is scattered over 100 W/m². Evapotranspiration requires three driving factors: an energy source, sufficient water for the vegetation, hot summer temperatures, and surface temperature. While the amount of water vapour travelling upward diffusion and evaporation increases, a relatively wet environment, vegetation cover in a dry environment, a lack of soil moisture, plant transpiration, and soil evaporation all contribute to an insufficient water supply [36, 37]. The study's findings [38] support the idea that a wetland ecosystem has a far wider range of variation in latent heat flux than a dryland environment.

Table 2. LE statistical results of 9 days were synthesized under different types of underlying surfaces

Site Name	Standard Deviation / (W/m ²)	Average / (W/m ²)	Maximum / (W/m ²)	Minimum / (W/m ²)	Kurtosis Partial	Degrees
station 1	162.35	154.12	661.32	-67.13	-0.28	0.91
station 12	180.83	164.91	627.27	-75.64	-0.69	0.23
Bajitan station	40.98	29.6	205.03	-56.5	2.99	1.6
Huazhaizi station	56.45	46.26	292.91	-71.79	2.34	1.55
Shenshawo station	39.28	29.90	201.23	-95.75	2.68	1.11
Wetland station	168.83	152.44	636.53	-23.52	-0.4	0.13

3.2. An analysis of the LE's intraday variation trend on several underlying surfaces

For numerous locations, the variance trend of the same site during LE days at various times was examined. Figure 5 shows that the variation trend across several sites was mostly stable within LE days. Bright days and less data loss, which are based on the climatic conditions at various points in June, July, and August, are the basis for the

lack of EC observation data. The usual days of 29 June, 13 July, and 27 August were used in order to further explore the variation trend of LE intraday at various locations on the same time scale (see Figure 6 for additional details). On June 29, the LE intraday trend lines at all stations were significantly influenced by the underlying surface. At 9:30, there were intermittent changes in each station's LE intraday trend lines. Now, the marshes, cornfields, and vegetable farms' LE intraday trend lines were increasing. Around noon, the value of the vegetable and cornfields reached its peak, following which the upward trend slowed. The minimum value was discernible at 12:30 and 13:00, respectively. The cornfield and vegetable area's broad horizontal vibration saw many peaks between 12:00 and 15:00. The intraday trend line for the wetland reached its peak at 13:00 and thereafter showed a tendency to oscillate and decline that was somewhat different from the trend lines for the cornfield and wetland. Throughout LE days, the same area was checked out at various times. Figure 5 shows that the variation trend across several sites was mostly stable within LE days. Bright days and less data loss, which are based on the climatic conditions at various points in June, July, and August, are the basis for the lack of EC observation data. The variance trend of LE intraday at various locations was further examined on typical days like June 29, July 13, and August 27. The LE intraday trend line patterns on July 13 varied slightly between the two sites.

Between 14:00 and 15:00, the average LE value in wetlands, vegetable fields, and cornfields achieved its peak value. The peak form was a single peak, the highest level in three months.

On the other hand, the average LE value for the dune, desert, and Gobi was at its lowest point in three months, and the trend line has a history of stability and low volatility. Only 33.69 W/m², 56.16 W/m², and 34.83 W/m² were the daily average LE values.

The diurnal fluctuation trend of LE at all locations on August 27 was nearly the same as it was on July 13 [40]. Vegetable land peak values dropped sharply from July to the lowest level in three months, followed by maize land and wetland peak values [41].

After carefully analysing the three days of data, it is evident that while there is little variation between each site's daily LE trend line on June 29, July 13, and August 27, there is a significant difference between the daily LE trend of different sites when compared to the other sites.

3.3. Analysis of LE Drivers for Various Types of Underlying Surface

In various underlying surface types, this section examines the link between LE and its driving components. According to Table 3 and the correlation coefficient data of each driving factor, the LE of this site is significantly correlated with the two driving factors: temperature and CO₂. According to the ranking of stations in Table 2, the correlation coefficients between temperature and LE were 0.72, 0.70, 0.31, 0.45, 0.39, and 0.68, respectively, and the link was very significant ($p < 0.01$). The link between CO₂ and LE was very significant ($p < 0.01$) and had correlation values of 0.64, 0.64, 0.28, 0.34, 0.18, and 0.65, respectively. The link between water vapour density and LE was either positive or negative depending on the area. Figure 7's regression curve demonstrates that when soil moisture levels are high, LE and temperature grow exponentially and at a far faster rate than when soil moisture levels are low. The temperature patterns of LE and CO₂ are comparable [42].

The Shenshaw station, which forms the base of the sand dune, is where the increase of LE with CO₂ occurs. This increase has a turning point that is obviously different from the monotonous change of CO₂ on the LE. In this work, stepwise regression analysis was used to create multiple regression equations using two drivers (air temperature and CO₂) that had strong association at each location.

3.4. Deficiencies and Discussions

Using EC observation data from the HiWATER test, this study analysed and examined the characteristics of evapotranspiration and the effects of various parameters on LE fluxes under diverse underlying surface types. The distribution and intradermal variation trend of latent heat flux change depending on the underlying surface characteristics of dry (dune, desert, Gobi) and wet (vegetable land, maize land, wetland), with vegetation cover having a stronger influence on latent heat flux.

Due to the short observation period of this experiment, the associated hydrological yearly frequency is singular, which may be impacted by the uneven distribution of rainfall throughout the year. In areas with dense vegetation, precipitation is typically more plentiful. Because plant roots store water, soil moisture is maintained, hence soil/plant moisture content is not the main factor limiting evapotranspiration.

Precipitation is minimal in thinly vegetated places. Since soil water is difficult to store and plant water content restricts evapotranspiration generation, it is swiftly supplied after precipitation while also rapidly evaporating [45]. This study found that

evapotranspiration in arid regions has no obvious relationship with each influencing factor, and the regularity of the associated data is significantly worse. As a result, the evapotranspiration model estimation containing vegetation cover has higher potential [46–48].

The findings from the analysis of climate, environment, and geomorphology are more conclusive and can serve as a trustworthy guide for the investigation of variables influencing agriculture irrigation, drainage, and evapotranspiration [49]. Latent heat flux under various underlying surface types is determined by a variety of factors, as is the degree of correlation. The relationship between the drivers and latent heat flux is not straightforwardly linear, and under dry conditions, the effect of CO₂ on latent heat flux approaches a critical level. On the research day selected for this study, the weather was sunny. Within a certain time following precipitation, the diurnal variation of ET is susceptible to observable mutation. However, the variation trend of latent heat flux under various weather conditions in June, July, and August in summer was not explored [27,51] due to the large influence of rainfall on the EC observation equipment [50]. Furthermore, there haven't been any research on latent heat flux or other climatic parameters [52].

4. Conclusions

Different underlying surface types will affect the latent heat flux distribution features when there is little fluctuation in the amount of surface plants and soil moisture.

In the same season, the diurnal variation trend of LE under various underlying surface types was statistically distinct from that of latent heat flux under the same underlying surface type. Crop midday depression influences latent heat flux when soil moisture levels are acceptable, and the change range is substantial. Low soil moisture causes a little shift in latent heat flow.

The link between temperature, CO₂, and latent heat flux is significant when soil water supply is adequate. The synergistic effect of temperature and CO₂ has a major impact on latent heat flow via plant transpiration and respiration when soil water availability is adequate.

In terms of time scale, all stations in the middle reaches of the Heihe River were reviewed and the relationship between influence variables and latent heat flux was examined in this study in June, July, and August 2012. As a result, more investigation

is needed to establish the function and impact of evapotranspiration in the transfer of surface energy and water circulation.

In terms of time scale, all stations in the middle reaches of the Heihe River were reviewed and the relationship between influence variables and latent heat flux was examined in this study in June, July, and August 2012. As a result, more investigation is needed to establish the function and impact of evapotranspiration in the transfer of surface energy and water circulation.

References

1. Chau, K. Use of Meta-Heuristic Techniques in Rainfall-Runoff Modelling. *Water* 2017, 9, 186. [CrossRef]
2. Zhang, Z.; Qin, H.; Yao, L.; Liu, Y.; Jiang, Z.; Feng, Z.; Ouyang, S. Improved Multi-objective Moth-flame Optimization Algorithm based on R-domination for cascade reservoirs operation. *J. Hydrol.* 2020, 581, 124431. [CrossRef]
3. Feng, F.; Li, X.; Yao, Y.; Liang, S.; Chen, J.; Zhao, X.; Jia, K.; Pintér, K.; McCaughey, J.H. An empirical orthogonal function-based algorithm for estimating terrestrial latent heat flux from eddy covariance, meteorological and satellite observations. *PLoS ONE* 2016, 11, e0160150. [CrossRef] [PubMed]
4. Wang, K.; Dickinson, R.E. A review of global terrestrial evapotranspiration: Observation, modeling, climatology, and climatic variability. *Rev. Geophys.* 2012, 50, RG2005. [CrossRef]
5. Wang, M.; Zhang, Y.; Lu, Y.; Gong, X.; Gao, L. Detection and attribution of reference evapotranspiration change (1951–2020) in the upper Yangtze River Basin of China. *J. Water Clim. Chang.* 2021, 12, 2624–2638. [CrossRef]
6. Priestley, C.H.B.; Taylor, R.J. On the Assessment of Surface Heat Flux and Evaporation Using Large-Scale Parameters. *Mon. Weather. Rev.* 1972, 100, 81–92. [CrossRef]
7. Talsma, C.J.; Good, S.P.; Jimenez, C.; Martens, B.; Fisher, J.B.; Miralles, D.G.; McCabe, M.F.; Purdy, A.J. Partitioning of evapotran

- spiration in remote sensing-based models. *Agric. For. Meteorol.* 2018, 260–261, 131–143. [CrossRef]
8. Yin, Y.; Wu, S.; Chen, G.; Dai, E. Attribution analyses of potential evapotranspiration changes in China since the 1960s. *Theor. Appl. Climatol.* 2010, 101, 19–28. [CrossRef]
9. Moazenzadeh, R.; Mohammadi, B.; Shahaboddin, S.; Chau, K.-W. Coupling a firefly algorithm with support vector regression to predict evaporation in northern Iran. *Eng. Appl. Comput. Fluid Mech.* 2018, 12, 584–597. [CrossRef]
10. Wang, Z.; Ye, A.; Wang, L.; Liu, K.; Cheng, L. Spatial and temporal characteristics of reference evapotranspiration and its climatic driving factors over China from 1979–2015. *Agric. Water Manag.* 2019, 213, 1096–1108. [CrossRef]
11. Zhang, R.; Xu, X.; Liu, M.; Zhang, Y.; Xu, C.; Yi, R.; Luo, W. Comparing evapotranspiration characteristics and environmental controls for three agroforestry ecosystems in a subtropical humid karst area. *J. Hydrol.* 2018, 563, 1042–1050. [CrossRef]
12. Zhang, Y.; Kang, S.; Ward, E.J.; Ding, R.; Zhang, X.; Zheng, R. Evapotranspiration components determined by sap flow and microlysimetry techniques of a vineyard in northwest China: Dynamics and influential factors. *Agric. Water Manag.* 2011, 98, 1207–1214. [CrossRef]
13. Barraza Bernadas, V.; Grings, F.; Restrepo-Coupe, N.; Huete, A. Comparison of the performance of latent heat flux products over southern hemisphere forest ecosystems: Estimating latent heat flux error structure using in situ measurements and the triple collocation method. *Int. J. Remote Sens.* 2018, 39, 6300–6315. [CrossRef]
14. Barraza, V.; Grings, F.; Franco, M.; Douna, V.; Entekhabi, D.; Restrepo-Coupe, N.; Huete, A.; Gassmann, M.; Roitberg, E. Estimation of latent heat flux using satellite land surface temperature and a variational data assimilation scheme over a eucalypt forest savanna in Northern Australia. *Agric. For. Meteorol.* 2019, 268, 341–353. [CrossRef]

15. Eswar, R.; Sekhar, M.; Bhattacharya, B.K. Comparison of three remote sensing based models for the estimation of latent heat flux over India. Hydrol. Sci. J.-J. Des. Sci. Hydrol. 2017, 62, 2705–2719. [CrossRef]