# **Supplementary Materials**

## Appendix A Basic information of reviewed papers

 Table A1 Basic information of reviewed papers

Citation	Geographica	l range <sup>1</sup>		Tempor	al range				Temperature indicator	UGS classification and identification			
Citation	Location	Climate zone	Year span	Sp <sup>2</sup>	Su <sup>2</sup>	Au <sup>2</sup>	Wi <sup>2</sup>	Туре	Data Source	Spatial Range <sup>3</sup>	UGS definition	Data Source <sup>4</sup>	Detailed Classification <sup>5</sup>
(Amani-Beni et al., 2019)	China - Beijing	Dwa	[M] 15y					LST	Landsat	Local neighborhood	LC	[F]SPOT	No
(An et al., 2022)	China - Beijing	Dwa	[S]					LST	Landsat	Central built-up area	LC	[F]GF	T/S/G
(Asgarian et al., 2014)	Iran - Isfahan	BWk	[S]	$\checkmark$				LST	Landsat	Central built-up area	LC	[C]Landsat	No
(Athukorala & Murayama, 2020)	Ghana - Accra	Aw	[M] 14y	$\checkmark$				LST	Landsat	Metropolitan area	LC	[C]Landsat	T/G
(Athukorala & Murayama, 2021)	Egypt - Cario	BWh	[M] 20y					LST	MODIS	Metropolitan area	LC	[C]Landsat	No
(Bao et al., 2016)	China - Baotou	BSk	[M] 15y		$\checkmark$			LST	Landsat	Central built-up area	LU	[C]Landsat	No
(Bartesaghi-Koc et al., 2020)	Australia - Sydney	Cfa	[S]		$\checkmark$		$\checkmark$	LST	Aerial Scanner	Local neighborhood	LC	[C]LiDAR	T/S/G
(Bera et al., 2022)	India - Kolkata	Aw	[S]	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	LST	Landsat	Central built-up area	LC	[F]GF	No
(Cai et al., 2022)	China - Fuzhou	Cfa	[M]10y		$\checkmark$			LST	Landsat	Central built-up area	LC	[C]Landsat	No
(Cao et al., 2010)	Japan - Nagoya	Cfa	[M] 5y	$\checkmark$	$\checkmark$	$\checkmark$		LST	ASTER	Central built-up area	LU	[F]IKONOS	T/S/G
(Chakraborti et al., 2019)	India - Hyderabad	BSh	[M] 13y			$\checkmark$		LST	Landsat	City boundary	LC	[C]Landsat	No
(Chen et al., 2014a)	China - Beijing	Dwa	[S]		$\checkmark$			LST	Landsat	Central built-up area	LC	[F]QuickBird	No
(Chen et al., 2014b)	China - Beijing	Dwa	[S]	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	LST	Landsat	Central built-up area	LC	[F]QuickBird	T/S/G
(D. Chen et al., 2022)	China - Urumqi	BWk	[S]		$\checkmark$			LST	Landsat	Central built-up area	LC	[F]PlanetScope	No
(J. Chen, P. Du, et al., 2022)	China – Nanjing	Cfa	[S]	$\checkmark$				LST	ASTER	Central built-up area	LC	[F]IKONOS	T only
(J. Chen, W. Zhan, et al., 2022)	China - Nanjing	Cfa	[S]	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	LST	Landsat	Central built-up area	LC	[F]IKONOS	T only
(Chen et al., 2020)	China - Nanjing	Cfa	[S]	$\checkmark$				LST	ASTER	Central built-up area	LC	[F]WorldView	T only
(J. Chen et al., 2021)	China - Nanjing	Cfa	[S]	$\checkmark$				LST	ASTER	Central built-up area	LC	[F]IKONOS, LiDAR	T/G
(X. Chen et al., 2022)	China - Guiyang	Cwa	[S]	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	LST	Landsat	Central built-up area	LC	[F]Google earth	No
(X. Chen et al., 2021)	China - Guiyang	Cwa	[S]					LST	Landsat	Central built-up area	LU	[F]Pleiades	No
(Cheng et al., 2015)	China - Shanghai	Cfa	[S]					LST	Landsat	Central built-up area	LU	[F]Aerial Image	No
(Connors et al., 2012)	US - Phoenix	BWh	[S]					LST	ASTER	City boundary	LC	[F]QuickBird	T/G
(Das et al., 2020)	India - Jaipur, Guwahati	BSh, Cwa	[M] 28y				$\checkmark$	LST	Landsat	City boundary	LC	[C]Landsat	No
(Du et al., 2022)	China - Xi'an	BSk	[S]					LST	Landsat	Central built-up area	LU	[F]Not specified	No
(Du et al., 2017)	China - Shanghai	Cfa	[S]					LST	Landsat	Central built-up area	LU	[F]Google earth	T/G
(Du et al., 2021)	China - Shanghai	Cfa	[S]					AT	Field Monitored	Central built-up area	LU	[F]Not specified	No
(Du et al., 2016)	China - Zhuhai	Cwa	[S]					LST	Landsat	Central built-up area	LC	[F]QuickBird	T/G
(Dugord et al., 2014)	Germany - Berlin	Dfb	[S]					LST	Landsat	City boundary	LU	[F]Governmental data	T/G
(Ekwe et al., 2020)	Nigeria - Port Harcourt	Am	[S]					LST	Landsat	Local neighborhood	LU	[F]Google earth	No
	Thailand - Bangkok,	Aw,											
(Estoque et al., 2017)	Indonesia - Jakarta,	Am,	[S]	$\checkmark$				LST	Landsat	Metropolitan area	LC	[C]Landsat	No
	Philippines - Manila	Aw											
	India - Mumbai, China -												
	Hong Kong, Kaohsiung,	Am Cwa Aw Aw											
(Fan et al., 2019)	Tainan, Singapore,	Af Af Am	[S]					LST	Landsat	City boundary	LC	[C]Landsat	T only
	Malaysia - Kuala Lumpur,	711, 711, 7111											
	Indonesia - Jakarta												
(Feng et al. 2020)	China - Naniing	Cfa	[M] &v	V			J	AT /	Landsat Meteorology Station	City houndary	IC	[C]I andsat	No
(1 cmg of al., 2020)	Cinna - manjilig	~1 <b>u</b>		v	v		v	LST	Landou, meteorology Station	City boundary	LC	[~]Lanasat	110
(Feng & Myint, 2016)	China - Beijing	Dwa	[S]					LST	ASTER	Central built-up area	LC	[F]QuickBird	No
								1					

Charles	Geographic	al range <sup>1</sup>		Tempo	ral range				Temperature indicator		UGS classification and identification		
Citation	Location	Climate zone	Year span	Sp <sup>2</sup>	Su <sup>2</sup>	Au <sup>2</sup>	Wi <sup>2</sup>	Туре	Data Source	Spatial Range <sup>3</sup>	UGS definition	Data Source <sup>4</sup>	Detailed Classification <sup>5</sup>
(Feyisa et al., 2014)	Ethiopia - Addis Ababa	Cwb	[S]			$\checkmark$		AT / LST	Landsat, Field Measured	Central built-up area	LU	[C]ASTER	T only
(Gage & Cooper, 2017)	US - Aurora	BSk	[S]		$\checkmark$			LST	Landsat		LC	[F]Publication: 1m	T/G
(Galletti et al., 2019)	US - Phoenix	BWh	[S]					LST	ASTER	Central built-up area	LC	[F]NAIP	T/G
	US - Austin, Baltimore,												
(Gao et al., 2022)	Chicago, Los Angeles, Portland	Cfa, Cfa, Csa, Csb	[M]4y mean		$\checkmark$			LST	Landsat	Central built-up area	LU	[F]NA	No
(Greene & Kedron, 2018)	Canada - Toronto	Dfa	[S]					LST	Landsat	City boundary	LC	[F]OuickBird	Tonly
(A. Guo et al., 2020)	China - Dalian	Dwa	[M] 11v					LST	Landsat	Central built-up area	LU	[C]Landsat	No
(G. Guo et al., 2020)	China - Guangzhou	Cwa	[S]					LST	Landsat	Central built-up area	LC	[F]Aerial Image	No
(0) 000 01 all, 2020)	China - Guangzhou	0	[~]					201	2	commencement up mon	20	[.]	
(Guo et al., 2021)	Shenzhen	Cwa	[S]		$\checkmark$			LST	Landsat	Central built-up area	LC	[F]Aerial Image	No
	China - Guangzhou,	Cwa Cfa Cwa											
(Guo et al., 2019)	Foshan, Dongguan, Shenzhen	Cwa	[S]		$\checkmark$		$\checkmark$	LST	Landsat	Central built-up area	LC	[F]Aerial Image	No
(He et al., 2021)	US - Baltimore, Boston	Cfa, Dfa	[M] 5y		$\checkmark$			LST	MODIS	Metropolitan area	LC	[C]NLCD	T only
(Hou & Estoque, 2020)	China - Hangzhou	Cfa	[S]					LST	Landsat	Metropolitan area	LC	[C]Landsat	T/G
(Hu et al., 2021)	China - Beijing	Dwa	[S]		$\checkmark$			LST	Landsat	Local neighborhood	LC	[F]GF	T/G
(Huang et al., 2018)	China - Harbin	Dwa	[M] 9y		$\checkmark$			LST	Landsat	Central built-up area	LU	[C]Landsat	No
(Huang et al., 2022)	China – Xi'an	BSk	[M]20y		$\checkmark$			LST	Landsat	Central built-up area	LU	[F]NA	No
(Huang & Wang, 2019)	China - Wuhan	Cfa	[S]	$\checkmark$	$\checkmark$		$\checkmark$	LST	Landsat	Central built-up area	LC	[F]ZY-3	T/G
(Jaganmohan et al., 2016)	Germany - Lipzig	Cfb	[S]		$\checkmark$			AT	Field Measured	Central built-up area	LU	[F]Not specified	T only
(Kamarianakis et al., 2017)	US - Phoenix	Bwh	[S]		$\checkmark$			AT	Meteorology Station	Metropolitan area	LC	[F]NAIP	T/G
(Karunaratne et al., 2022)	Nepal - Kathmandu	Cwa	[M]20y					LST	Landsat	Metropolitan area	LC	[C]Landsat	T/G
(Ke et al., 2021)	China - Wuhan	Cfa	[M] 3y		$\checkmark$			LST	Landsat	Central built-up area	LC	[C]FROM-GLC10	No
(Kim et al., 2016)	US - Austin	Cfa	[S]		$\checkmark$			LST	Landsat	Central built-up area	LC	[F]Aerial Image	T/G
(Kong, Yin, James, et al., 2014)	China - Nanjing	Cfa	[S]		$\checkmark$			LST	Landsat	Central built-up area	LC	[F]IKONOS	T/G
(Kong, Yin, Wang, et al., 2014)	China - Nanjing	Cfa	[S]		$\checkmark$			LST	Landsat	Central built-up area	LC	[F]IKONOS	T/G
												[C]ASTER, LANDSAT,	
(Kowe et al., 2021)	Zimbabwe - Harare	Cwb	[M] 23y		V			LST	ASTER, Landsat	City boundary	LC	Sentinel	No
(Lemoine-Rodríguez et al., 2022)	Mexico - Xalapa	Cfb	[S]	$\checkmark$				LST	Landsat	Central built-up area	LC	[F]SPOT	T/G
(Li et al., 2017)	US - Phoenix	BWh	[S]		$\checkmark$			LST	MASTER	Central built-up area	LC	[F]NAIP	T/G
(B. Li et al., 2020)	China - Zhengzhou	Cwa	[S]	$\checkmark$				LST	Landsat	Central built-up area	LU	[F]Google earth	No
(Li et al., 2018)	China - Xi'an	BSk	[M] 25y		$\checkmark$			LST	Landsat	Central built-up area	LC	[C]Landsat	No
	Bangladesh - Dhaka,												
(Li et al., 2022)	India - Kolkata, Thailand	Aw	[M] 20y	$\checkmark$			$\checkmark$	LST	Landsat	Central built-up area	LC	[C]Landsat	No
	- Bangkok												
(Li et al., 2011)	China - Shanghai	Cfa	[S]	$\checkmark$	$\checkmark$			LST	Landsat	Central built-up area	LU	[F]Aerial Image	No
(T. Li et al., 2020)	China - Beijing	Dwa	[S]		$\checkmark$			LST	Landsat	Central built-up area	LC	[F]IKONOS	T/G
(Li et al., 2013)	China - Beijing	Dwa	[S]					LST	Landsat	Central built-up area	LC	[F+C]QuickBird, SPOT,	No
(Li et al., 2012)	China - Beiiing	Dwa	[S]					LST	Landsat	Central built-un area	LC	[F]SPOT	No
(T. Li et al., 2021)	China - Beijing	Dwa	[S]			, V		LST	Landsat	Central built-up area	LC	[F]IKONOS	T/G
(Y. Li et al., 2020)	China - Beijing	Dwa	[S]		V		, √	AT	Field Measured	Local neighborhood	LC	[F]GF	T/G
(Y Lietal 2021)	China - Reijing	Dwa	[S]		, √		,	ΔТ	Field Measured	Central huilt-un area	LU	[F]GF	No
(1. Li Ci al., 2021)	Suma - Dolling	Dwa	[0]		v			2		Contrat built-up alea		[1]01	110

Citation	Geographica	al range <sup>1</sup>		Tempo	ral range				Temperature indicator		UGS classification and identification		
	Location	Climate zone	Year span	Sp <sup>2</sup>	Su <sup>2</sup>	Au <sup>2</sup>	Wi <sup>2</sup>	Туре	Data Source	Spatial Range <sup>3</sup>	UGS definition	Data Source <sup>4</sup>	Detailed Classification
(Li et al., 2019)	China - Shanghai	Cfa	[S]		$\checkmark$			LST	Landsat	Central built-up area	LC	[F]Governmental data	No
(W. Liu et al., 2022)	China - Beijing	Dwa	[S]			$\checkmark$		LST	Landsat	Central built-up area	LC	[C]FROM-GLC10	No
(Liu et al., 2021)	China - Xuchang	Cwa	[S]		$\checkmark$			LST	Landsat	Central built-up area	LU	[C]Landsat	No
(K. Liu et al., 2022)	China - Shijiazhuang	BSk	[S]		$\checkmark$			LST	Aerial Scanner, Landsat, MODIS	Central built-up area	LC	[F]Aerial Image	T/G
(Liu et al., 2016)	China - Beijing	Dwa	[S]		$\checkmark$	$\checkmark$	$\checkmark$	LST	Landsat	Central built-up area	LC	[F]GF	T/G
(H. Liu & Q. Weng, 2009)	US - Indianapolis	Dfa	[M] 6y	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	LST	Aster	Metropolitan area	LC	[C]ASTER	T/G
(S. Liu et al., 2022)	China - Fuzhou	Cfa	[M] 16y	$\checkmark$	$\checkmark$			LST	Landsat	Central built-up area	LC	[C]Landsat	No
(Wenrui Liu et al., 2022)	China - Beijing	Dwa	[S]			$\checkmark$		LST	Landsat	Central built-up area	LC	[C]Landsat + ESA	No
(Liu et al., 2018a)	China - Shenzhen	Cwa	[M] 28y		$\checkmark$	$\checkmark$	$\checkmark$	LST	Landsat	Central built-up area	LC	[C]Landsat	No
(Liu et al., 2018b)	China - Shenzhen	Cwa	[M] 28y		$\checkmark$			LST	Landsat	Central built-up area	LC	[C]Landsat	No
(Lu et al., 2012)	China - Chongqing	Cfa	[S]		$\checkmark$			AT	Field Measured	Local neighborhood	LU	[F]Not specified	No
(Lu et al., 2020)	China - Xi'an	BSk	[M] 25y	$\checkmark$				LST	Landsat	Central built-up area	LC	[C]Landsat	No
(Lyu et al., 2023)	China - Yinchuan	BWk	[S]		$\checkmark$			LST	Landsat	Central built-up area	LC	[C]Sentinel	No
(Ma & Peng, 2022)	China - Kunming	Cwb	[M] 28y	$\checkmark$				LST	Landsat	City boundary	LC	[C]Landsat	No
(Ma et al., 2021)	China - Xi'an	BSk	[M] 9y		$\checkmark$			LST	Landsat	Central built-up area	LC	[C]Landsat	T/G
(Maimaitiyiming et al., 2014)	China - Aksu	BWk	[S]		$\checkmark$			LST	Landsat	Central built-up area	LC	[C]Landsat	No
(Masoudi & Tan, 2019)	Singapore - Singapore	Af	[M] 42y					LST	Landsat	City boundary	LC	[C]Landsat	No
(Masoudi et al., 2021)	Singapore - Singapore	Af	[M] 10y					LST	Landsat	City boundary	LC	[C]Landsat, Governmental data	No
	Malaysia - Kuala Lumpur,	Af,											
	Indonesia - Jakarta,	Am,											
(Masoudi et al., 2019)	China - Hong Kong,	Cwa,	[S]					LST	Landsat	City boundary	LC	[C]Landsat	No
	Singapore - Singapore	Af											
	China - Beijing.												
(Naeem et al., 2018)	Pakistan - Islamabad	Dwa, Cwa	[S]					LST	Landsat	Central built-up area	LC	[F]GF	No
	China - Beijing, Tianiin,	Dwa, Dwa, BSk.											
(Pang et al., 2022)	Xi'an. Zhengzhou	Cwa	[S]					LST	Landsat	Central built-up area	LU	[F]Google earth	No
(Park & Cho, 2016)	Koear - Ulsan	Cfa	[S]		$\checkmark$			LST	Landsat	Central built-up area	LU	[C]Landsat	No
(Peng et al., 2021)	China - Shenzhen	Cwa	[S]			$\checkmark$		LST	Landsat	Central built-up area	LU	[F]Governmental data	No
(Peng et al., 2018)	China - Shenzhen	Cwa	[S]	$\checkmark$				LST	Landsat	Central built-up area	LC	[F]Governmental data	T/G
(Peng et al., 2016)	China - Beijing	Dwa	[S]		$\checkmark$			LST	Landsat	City boundary	LC	[C]Landsat	No
(Pramanik & Punia, 2019)	India - Delhi	BSh	[S]					LST	Landsat	Central built-up area	LC	[C]Sentine]	T/G
(Oian et al., 2018)	China - Beijing	Dwa	[S]		$\checkmark$			AT	Field Monitored	Local neighborhood	LC	[F]Google earth	No
(Qiu & Jia. 2020)	China - Beijing	Dwa	[S]						Landsat	Central built-up area	LU	[F]Worldview	10
(Rahimi et al., 2021)	Iran - Tehran	BSk	[S]					LST	Landsat	Central built-up area	LC	[C]Landsat	No
(Rakoto et al., 2021)	Australia - Melbourne	Cfb	[S]		1			LST	Landsat	Central built-up area	LC	[F]LiDAR	DC
(Ren et al., 2013)	China - Changchun	Dwa	[S]		1			LST	Landsat	Central built-up area	LU	[F]SPOT	No
(Ren et al. 2014)	China - Changchun	Dwa	[5]		۰ ٦			LST	Landsat	Central built-up area	LC	[F]SPOT	No
(Reference $al_{2014}$ )	US - Denver	BSk	[5]		1			LST	Landsat	Local neighborhood	LC	[F]L iDAR	T/G
(Roubi et al. 2018)	Iran - Sari	Csa	[5]	·	1	,		LST	Landsat	Metropolitan area	LC	[C]I andsat	No
(Shah et al. 2021)	India - Remmoalum	Aw	[5]		,			LST	Landsat	Central huilt-un area	LU	[C]Landsat	No
(Shaker et al. $2021$ )	IIS - New Vork	Dfa	[5]	v		J		٨T	Meteorology Station	Central built_up area		[F]NVCPP · 0 01/m	T/G
(Shi & $7h_{20}$ , 2022)	China - Vi'an	BSh	[5]		1	v		AI LOT	I andeat	Central built up area		[1] [1] 1 CI K. 0.714111 [C] Sentine!	1/G
(Shih 2017)	China - Al all	Dok	[3] [5]		N			LOI	Landsat	Central built we area	IC	[C]I andsat	I/U
(Shih, 2017)	China - Taipei	Cia	[3]		N			LOT	Landaat	Control location		[C]Landaat	INU
(SIIIII, 2010)	Unina - Taipei	Cla	[5]		N			L91	Landsat	Central built-up area	LL	ULandsat	1N0

LubitIonalIonalIonalSpatialSpatialUsed-setIonal-MoneIonal	~	Geographic	al range <sup>1</sup>		Tempo	ral range				Temperature indicator	UGS classification and identification			
	Citation	Location	Climate zone	Year span	Sp <sup>2</sup>	Su <sup>2</sup>	Au <sup>2</sup>	Wi <sup>2</sup>	Туре	Data Source	Spatial Range <sup>3</sup>	UGS definition	Data Source <sup>4</sup>	Detailed Classification <sup>5</sup>
Image         Image <t< td=""><td></td><td>Nigeria - Lagos, Kenya -</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></t<>		Nigeria - Lagos, Kenya -												
Image in the image interm of the image into a set of the image. The image is the image into a set of the image into a set of the image. The image is the image into a set of the image into a set of the image into a set of the image. The image is the image is the image into a set of the image into a set of the image. The image is the image is the image is the image is the image. The image is the image is the image is th	(Simwanda et al., 2019)	Nairobi, Ethiopia - Addis	Aw, Cfb, Cwb, Cwa	[S]		$\checkmark$		$\checkmark$	LST	Landsat	Metropolitan area	LC	[C]Landsat	No
Image of the stand (a) and b)		Ababa, Zambia - Lusaka												
Image	(Song et al., 2020)	China - Hangzhou	Cfa	[S]	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	LST	Landsat	Metropolitan area	LC	[F]SPOT	T/G
Monet       Constration     Monet     Monet     Monet     Monet     Monet     Monet     Monet     Monet       Constration     Monet     Monet     Monet     Monet     Monet     Monet     Monet     Monet       Constration     Monet     Monet     Monet     Monet     Monet     Monet     Monet       Constration     Monet     Monet     Monet     Monet     Monet     Monet     Monet       Constration     Monet     Monet     Monet     Monet     Monet     Monet     Monet       Monet     Monet     Monet     Monet     Monet     Monet     Monet     Monet       Monet     Monet     Monet     Monet     Monet     Monet     Monet     Monet     Monet       Monet     Monet     Monet     Monet     Monet     Monet     Monet     Monet     Monet       Monet     Monet     Monet     Monet     Monet     Monet     Monet     Monet       Monet     Monet     Monet     Monet     Monet     Monet     Monet       Monet     Monet <td>(Xiang Sun et al., 2020)</td> <td>China - Nanjing</td> <td>Cfa</td> <td>[M] 8y</td> <td></td> <td><math>\checkmark</math></td> <td></td> <td></td> <td>LST</td> <td>Landsat</td> <td>Central built-up area</td> <td>LU</td> <td>[F]Google earth</td> <td>No</td>	(Xiang Sun et al., 2020)	China - Nanjing	Cfa	[M] 8y		$\checkmark$			LST	Landsat	Central built-up area	LU	[F]Google earth	No
<table-container>      Image in the sector of the</table-container>	(Sun et al., 2021)	China – Shanghai	Cfa	[S]		$\checkmark$			LST	Landsat	Central built-up area	LU	[F]Google earth	T/G
<table-container>      Index     Index</table-container>	(Sun et al., 2022)	China - Chengdu	Cfa	[M]29y	$\checkmark$				LST	Landsat	Central built-up area	LC	[C]Landsat	T/G
<table-container>      Arm and and the symmetry of the symmetry of</table-container>	(Tan & Li, 2013)	China - Beijing	Dwa	[S]		$\checkmark$			LST	Landsat	Central built-up area	LC	[C]Landsat	No
Image of Auge     Canabia     Canabi	(X. Tan et al., 2021)	China - Nanning	Cfa	[M] 4y			$\checkmark$		LST	Landsat	Central built-up area	LC	[C]Landsat	No
<table-container>      Index     Index     Main     Main</table-container>	(Tang et al., 2023)	China - Wuhan	Cfa	[S]		$\checkmark$			LST	Landsat	Central built-up area	LC	[C]FROM-GLC10 10m, EULUC land use	No
Image	(Terfa et al., 2020)	Ethiopia - Addis Ababa	Cwb	[M]22y					LST	Landsat	City boundary	LC	[C]Landsat	No
Image is a series of the series of	(Vaz Monteiro et al., 2016)	UK - London	Cfb	[S]		$\checkmark$			AT	Field Monitored	Local neighborhood	LU	[F]Not specified	T/G
	(Wang & Zhou, 2022)	China - Beijing	Dwa	[M] 5y		$\checkmark$			LST	MODIS	Central built-up area	LC	[F]SPOT, ALOS	T/G
Image: Probability of the sector of the s		China - Beijing,												
Scrummer, bar with the second	(Wang et al., 2023)	Shenzhen, US -	Dwa, Cwa, Csa, Cfa	[S]		$\checkmark$			LST	Landsat	Central built-up area	LC	[F]Publication: 1m	T only
Partial Partial Partial Partial 		Sacramento, Baltimore												·
Image of the symplex     Properties     First     Left     Index     Metropolata area     LC     [I]Landsat     First       (Wang et al., 2022)     China -Shangbai     Gran     IS1     Image of the symplex     Image of the		China - Nanjing, Wuhan,												
Mage at 2020     China - Shanghai     Circl     Sin     Jeader     Canaba     Canaba     Fight mapped     No       (Wang at 2.018)     China - Baingano     Gan     Sin     Sin     Sin     Landarto     Canaba Unique area     Lice     IPAA     No       (Wang at 2.021)     China - Baingano     Sina	(Wang et al., 2020)	Chongqing	Cfa	[M]19y		N			LST	Landsat	Metropolitan area	LC	[F]Landsat	T/G
(Mag et al., 2013)Chian - BangaboChian[S]NLessLandsatCentral bailuity areaL[F]ANo(X. Wang et al., 2021)Chian - BaiyanByan[S]NLLSTLandsatCentral bailuity areaLC[P]SPOTTG(Y. Wang et al., 2021)Chian - BaiyanGrama- LippicChian - BaiyanSiLSTLandsatCentral bailuity areaLC[P]SPOTTG(Weber et al., 2014)Gramany-LippicChian - Chian - MangaboSiSiLSTLandsatCentral bailuity areaInduser Bained and SiNo(Weber et al., 2014)Chian - ShanyanChianSiSiSiLSTLandsatCentral bailuity areaInduser Bained and SiNo(Weber et al., 2024)Chian - ShanyanChianSiSiSiLSTLandsatCentral bailuity areaILC[C]CRPRANo(Wat et al., 2024)Chian - ShanyanChianSiSiLSiLandsatCentral bailuity areaILC[C]AndsatNo(Wat et al., 2024)Chian - ShanyanChianSiSiLandsatCentral bailuity areaILC[C]AndsatNo(Q. Wat et al., 2024)Chian - ShanyanChian - ShanyanSiSiLandsatCentral bailuity areaILC[C]AndsatSi(Q. Wat et al., 2024)Chian - ShanyanChian - ShanyanSiSiLandsatCentral bailuity areaILC[C]AndsatSi(Q. Wat et al	(Wang et al., 2022)	China - Shanghai	Cfa	[S]		$\checkmark$			LST	Landsat	Central built-up area	LU	[F]Amap	No
K. Wang et al., 2021)China - BeigingNumberSignSign $\sqrt{4}$ $\sqrt{5}$ <th< td=""><td>(Wang et al., 2018)</td><td>China - Changzhou</td><td>Cfa</td><td>[S]</td><td><math>\checkmark</math></td><td></td><td></td><td></td><td>LST</td><td>Landsat</td><td>Central built-up area</td><td>LU</td><td>[F]NA</td><td>No</td></th<>	(Wang et al., 2018)	China - Changzhou	Cfa	[S]	$\checkmark$				LST	Landsat	Central built-up area	LU	[F]NA	No
(Name et al. 2021)(Name - Injury)(BS)(S)<	(X. Wang et al., 2021)	China - Beijing	Dwa	[S]		$\checkmark$			LST	Landsat	Central built-up area	LC	[F]SPOT	T/G
Weber et al. 2014)Gramay-LipzigChSSSArial ScamerCity boundaryInduce*land out[F]GovernanetladianNo(Weber et al. 2014)Cita-SungabouCau[S]VVATMetropolitan constraintsCity boundaryLC[C]GERSANo(Weber et al. 2014)US - KanserCita StandiantCita StandiantCita StandiantCita StandiantCita StandiantCita StandiantNo(Wet et al. 2021)Citan StandiantCita[S]VVLSLaddiantCita StandiantNo(Wet et al. 2024)Citan SundiantCita[S]VVLSLaddiantCita StandiantNo(Wet et al. 2024)Citan StandiantCita[S]VVLSLaddiantCita StandiantNo(Wet et al. 2024)Citan StandiantCita[S]VVLSLaddiantCita StandiantNo(Wet et al. 2024)Cita StandiantCita[M]VVLSLaddiantCita StandiantCita StandiantNo(Wet et al. 2024)Cita StandiantCita[M]VVLSLaddiantCita StandiantCita StandiantCita StandiantNo(Wet et al. 2020)Cita StandiantCita[S]VVLSLaddiantCita StandiantCita StandiantCita StandiantNo(Yet et al. 2020)Cita StandiantStandiant[S]VVLSLaddiantCita Stand	(Y. Wang et al., 2021)	China - Taiyuan	BSk	[S]		$\checkmark$			LST	Landsat	Central built-up area	LU	[C]Governmental data	T/G
(Wen et al., 2011)China - GuangzhouCwa(Si $$ $$ ATMeteorology StationGity boundaryLC[C] CBERSNo(Wet et al., 2021)Cis - Skmask CityDía[Si $$ LLadatMetorology StationCico - Central bailt-guareaLC[C] CBERSNo(Wu et al., 2021)China - MingzhouCfa[Si $$ LSLadastCentral bailt-guareaLC[C] HadastNo(Q. Wu et al., 2022)China - HangzhouCfa[Si $$ LSLadastCentral bailt-guareaLC[C] LadastNo(Wu et al., 2022)China - HangzhouCfa[M] 20 $$ LSLadastCentral bailt-guareaLC[C] LadastNo(Wu et al., 2022)China - ShenzhenCfa[M] 20 $$ LSLadastCentral bailt-guareaLC[C] LadastNo(Wu et al., 2023)China - ShenzhenCfa[M] 20 $$ LSLadastCentral bailt-guareaLC[C] LadastNo(Xi et al., 2017)China - ShenzhenCwa[S] $$ LSLadastCity boundaryLC[C] LadastTG(Yan et al., 2017)China - ShenzhenCwa[S] $$ LSLadastCentral bailt-guareaLC[F] Adast[F] Adast(Yan et al., 2017)China - ShenzhenCwa[S] $$ LSLadastCentral bailt-guareaLC[F] Adast[F] Adast(Yan et al., 201	(Weber et al., 2014)	Germany - Lipzig	Cfb	[S]			$\checkmark$		LST	Aerial Scanner	City boundary	land use*land use	[F]Governmental data	No
(Wesley & A. Brunsell, 2019)US - Kanasa GrityDín(M] 3y $$ LSTLadsatMetropolitan ceraLC[C]NRINo(Wu et al., 2021)China - ShanghuiCfa[S] $$ LSTLadsatCeriral built-up reaLU[C]LandsatNo(Wu et al., 2021)China - BuilgingDava[S] $$ LSTLadsatCeriral built-up reaLC[C]RRINo(Q. Wu et al., 2022)China - BuilgingDava[S] $$ LSTLadsatCeriral built-up reaLC[C]LandsatTG(Wu et al., 2024)China - SuzhouCfa[M] 2y $$ LSTLadsatCeriral built-up reaLC[C]LandsatNo(Wu et al., 2024)China - SuzhouCfa[M] 2y $$ LSTLadsatCeriral built-up reaLC[C]LandsatNo(Wu et al., 2024)China - SuzhouCfa[M] 2y $$ LSTLadsatCiral built-up reaLC[C]LandsatNo(Ki et al., 2017)China - SuzhouCfa[S] $$ $$ LSTLadsatCiral built-up reaLC[C]LandsatNo(Ya et al., 2017)China - BuilgingDava[S] $$ $$ LSTLadsatCiral built-up reaLC[C]LandsatNo(Ya et al., 2017)China - BuilgingDava[S] $$ $$ LSTLadsatCiral built-up reaLC[F]SPCTNo(Ya et al., 2017)China - Bu	(Wen et al., 2011)	China - Guangzhou	Cwa	[S]			$\checkmark$		AT	Meteorology Station	City boundary	LC	[C]CBERS	No
(Wu et al., 2021)China - ShanghainCfa[S1 $$ LSTLandsatCentral built-up areaLU(C] LandsatNo(Wu et al., 2024)China - BeijingDwa[S1 $$ LSTHJ-1BCity boundaryLC[C]HJ-1BNo(Wu et al., 2022)China - BanghouCfa[M] 20 $$ LSTLandsatCentral built-up areaLC[C]LandsatTG(Wu et al., 2022)China - BanghouCfa[M] 20 $$ LSTLandsatCentral built-up areaLC[C]LandsatTG(Wu et al., 2022)China - ShenzhenCfa[M] 20 $$ LSTLandsatCentral built-up areaLC[C]LandsatTG(Wu et al., 2020)China - ShenzhenCfa[M] 10y $$ LSTLandsatCentral built-up areaLC[C]LandsatTG(Xu et al., 2017)China - BeijingCwa[S1 $$ LSTLandsatCentral built-up areaLC[C]LandsatTG(Yan et al., 2017)China - BeijingDwa[S1 $$ LSTLandsatCentral built-up areaLC[F]APIData(Yan et al., 2017)China - BeijingDwa[S1 $$ $$ LSTLandsatCentral built-up areaLC[F]APIData(Yan et al., 2017)China - BeijingDwa[S1 $$ $$ LSTLandsatCentral built-up areaLC[F]APIData(Yan et al., 2021)China - Gha	(Wesley & A. Brunsell, 2019)	US - Kansas City	Dfa	[M] 3y		$\checkmark$			LST	Landsat	Metropolitan area	LC	[C]NRI	No
(Wu et al., 2014)China - WuhanCfa(Si $$ LSTHJ-IBCity boundaryLC(CHJ-1BNo(Q. Wu et al., 2022)China - BeijingDva(Si $$ LSTLandsatCentral built-up areaLC(CJR-M-GLC10)T/G(Wu et al., 2022)China - HangzhouCfa(M1 20) $$ LSTLandsatCentral built-up areaLC(CJR-M-GLC10)T/G(Wu et al., 2023)China - ShanzhouCfa(M1 20) $$ LSTLandsatCentral built-up areaLC(CJL-andsatT/G(Ku et al., 2013)China - ShanzhouCwa(M1 0) $$ LSTLandsatCity boundaryLC(CJL-andsatT/G(Xu et al., 2017)China - ShenzhouCwa(M1 0) $$ $$ LSTLandsatCentral built-up areaLC(FJA-ufstatT/G(Yan et al., 2017)China - BeijingDva(SI $$ $$ LSTLandsatCentral built-up areaLC(FJA-ufstatT/G(Yan et al., 2017)China - BeijingDva(SI $$ $$ LSTLandsatCentral built-up areaLC(FJA-UfstatT/G(Yan et al., 2017)China - ChangehunDva(SI $$ $$ LSTLandsatCentral built-up areaLC(FJA-UfstatT/G(Yan et al., 2021)China - ChangehunDva(SI $$ $$ LSTLandsatCentral built-up areaLC(FJGF <t< td=""><td>(Wu et al., 2021)</td><td>China - Shanghai</td><td>Cfa</td><td>[S]</td><td></td><td><math>\checkmark</math></td><td></td><td></td><td>LST</td><td>Landsat</td><td>Central built-up area</td><td>LU</td><td>[C]Landsat</td><td>No</td></t<>	(Wu et al., 2021)	China - Shanghai	Cfa	[S]		$\checkmark$			LST	Landsat	Central built-up area	LU	[C]Landsat	No
Q. Wu et al., 2022)China - BeijingDwa[S] $$ LSTLandsatCentral built-up areaLC[C]FROM-GLC10TG(Y. Wu et al., 2022)China - HangzhouCfa[M] 20 $$ LSTLandsatMetropolitan areaLC[C]LandsatTG(Wu & Zhang, 2018)China - ShanzhonCfa[S] $$ LSTLandsatCentral built-up areaLC[C]LandsatNo(Xie et al., 2020)China - ShenzhonCau[S] $$ LSTLandsatCity boundaryLC[C]LandsatTG(Xie et al., 2017)China - ShenzhonCau[S] $$ $$ LSTLandsatCentral built-up areaLG[C]LandsatTG(Yan et al., 2017)China - BeijingDwa[S] $$ $$ LSTLandsatCentral built-up areaLC[F]NAIPTG(Yan et al., 2017)China - BeijingDwa[S] $$ $$ LSTLandsatCentral built-up areaLC[F]NAIPNo(Yan et al., 2017)China - AneguhanDwa[S] $$ $$ LSTLandsatCentral built-up areaLC[F]SDATNo(Yang te al., 2021)China - ChangchunDwa[S] $$ $$ LSTLandsatCentral built-up areaLC[F]GFNo(Yang te al., 2021)China - ChangchunDwa[S] $$ $$ LSTLandsatCentral built-up areaLC[F]GFNo <td>(Wu et al., 2014)</td> <td>China - Wuhan</td> <td>Cfa</td> <td>[S]</td> <td></td> <td><math>\checkmark</math></td> <td></td> <td></td> <td>LST</td> <td>HJ-1B</td> <td>City boundary</td> <td>LC</td> <td>[C]HJ-1B</td> <td>No</td>	(Wu et al., 2014)	China - Wuhan	Cfa	[S]		$\checkmark$			LST	HJ-1B	City boundary	LC	[C]HJ-1B	No
(Y. Wu et al., 2022)China - HangzhouCfa[M] 20y $$ LSTLandsatMetropolitan areaLC[C] LandsatT/G(Wu & Zhang, 2018)China - SuzhouCfa[S] $$ LSTLandsatCentral built-up areaLC[C] LandsatNo(Xi et al., 2020)China - ShenzhenCwa[M] 10y $$ LSTLandsatCity boundaryLC[C] LandsatT/G(Xi et al., 2017)China - BeijingDwa[S] $$ $$ LSTLandsatCity boundaryLC[C] LandsatT/G(Yan et al., 2017)China - BeijingDwa[S] $$ $$ LSTLandsatCentral built-up areaLU[C] LondsatT/G(Yan et al., 2017)China - BeijingDwa[S] $$ $$ LSTLandsatCentral built-up areaLC[F] NAIPD/G(Yan et al., 2017)China - BeijingDwa[S] $$ $$ LSTLandsatCentral built-up areaLC[F] SPOTNo(Yan, Et al., 2021)China - ChangchunDwa[S] $$ $$ LSTLandsatCentral built-up areaLC[F] SPOTNo(Yang et al., 2021)China - ChangchunDwa[S] $$ $$ LSTLandsatCentral built-up areaLC[F] SPOTNo(Yang et al., 2021)China - ChangchunDwa[S] $$ $$ LSTLandsatCentral built-up areaLC	(Q. Wu et al., 2022)	China - Beijing	Dwa	[S]		$\checkmark$			LST	Landsat	Central built-up area	LC	[C]FROM-GLC10	T/G
(Wu & Zhang, 2018)China - SuzhouCfa[S] $$ LSTLandsatCentral built-up areaLC[C] LandsatNo(Xie et al., 2020)China - ShenzhenCwa[M] 10y $$ LSTLandsatCity boundaryLC[C] LandsatT/G(Xie et al., 2013)China - ShenzhenCwa[S] $$ $$ LSTLandsatCity boundaryLC[C] LandsatT/G(Xu et al., 2017)China - BeijingDwa[S] $$ $$ LSTLandsatCentral built-up areaLQ[F] AugebrillT/G(Yan et al., 2017)China - BeijingDwa[S] $$ $$ LSTLandsatCentral built-up areaLC[F] AugebrillT/G(Yan et al., 2017)China - BeijingDwa[S] $$ $$ LSTLandsatCentral built-up areaLC[F] AugebrillT/G(Yan et al., 2021)China - ChangehunDwa[S] $$ $$ LSTLandsatCentral built-up areaLC[F] GFNo(Yang, Fe, Yu, et al., 2017)China - ChangehunDwa[S] $$ $$ LSTLandsatCentral built-up areaLC[F] GFNo(Yang et al., 2021)China - ChangehunDwa[S] $$ $$ LSTLandsatCentral built-up areaLC[F] GFNo(Yang et al., 2021)China - ChangehunDwa[S] $$ $$ LSTLandsatCentral built-	(Y. Wu et al., 2022)	China - Hangzhou	Cfa	[M] 20y		$\checkmark$			LST	Landsat	Metropolitan area	LC	[C]Landsat	T/G
(Xie et al., 2020)China - ShenzhenCwa[M] 10y $$ LSTLandsatCity boundaryLC[C] LandsatT/G(Xie et al., 2013)China - ShenzhenCwa[S] $$ LSTLandsatCity boundaryLC[C] LandsatT/G(Xu et al., 2017)China - BeijingDwa[S] $$ LSTLandsatCentral built-up areaLU[F] QuickBirdT/G(Yan et al., 2019)US - PhoenixBWh[S] $$ $$ LSTLandsatCentral built-up areaLC[F] SPOTNo(Yan et al., 2021)China - BeijingDwa[S] $$ $$ LSTLandsatCentral built-up areaLC[F] SPOTNo(Yang, He, Wang, et al., 2017)China - ChangchunDwa[S] $$ $$ LSTLandsatCentral built-up areaLC[F] SPOTNo(Yang, et al., 2021)China - ChangchunDwa[S] $$ $$ LSTLandsatCentral built-up areaLC[F] GFNo(Yang, et al., 2021)China - ChangchunDwa[S] $$ $$ LSTLandsatCentral built-up areaLC[F] GFNo(Yang et al., 2021)China - ChangchunDwa[S] $$ $$ LSTLandsatCentral built-up areaLC[F] GFNo(Yang et al., 2021)China - ChangchunDwa[S] $$ $$ $$ LSTLandsatCentral built-up area </td <td>(Wu &amp; Zhang, 2018)</td> <td>China - Suzhou</td> <td>Cfa</td> <td>[S]</td> <td><math>\checkmark</math></td> <td></td> <td></td> <td></td> <td>LST</td> <td>Landsat</td> <td>Central built-up area</td> <td>LC</td> <td>[C]Landsat</td> <td>No</td>	(Wu & Zhang, 2018)	China - Suzhou	Cfa	[S]	$\checkmark$				LST	Landsat	Central built-up area	LC	[C]Landsat	No
Kie et al., 2013)China - ShenzhenCwa[S] $$ LSTLandsatCity boundaryLC[C] Landsat[T/G(Xu et al., 2017)China - BeijingDwa[S] $$ LSTLandsatCentral built-up areaLU[F]QuickBirdT/G(Yan et al., 2019)US - PhoenixBWh[S] $$ $$ LSTLandsatCentral built-up areaLC[F]ALP[F]ALPT/G(Yan et al., 2021)China - BeijingDwa[S] $$ $$ LSTLandsatCentral built-up areaLC[F]SPOTNo(Yang, He, Yu, et al., 2017)China - ChangchunDwa[S] $$ $$ LSTLandsatCentral built-up areaLC[F]GFNo(Yang et al., 2021)China - ChangchunDwa[S] $$ $$ LSTLandsatCentral built-up areaLC[F]GFNo(Yang et al., 2021)China - ChangchunDwa[S] $$ $$ LSTLandsatCentral built-up areaLC[F]GFNo(Yang et al., 2021)China - ChangchunDwa[S] $$ $$ LSTLandsatCentral built-up areaLC[F]Governmental dataT/G(Yang et al., 2022)Denmark - CopenhageDb[S] $$ $$ LSTLandsatCentral built-up areaLC[F]Governmental dataT/G(Yang et al., 2022)Denmark - CopenhageDb[S] $$ $$ LSTLand	(Xie et al., 2020)	China - Shenzhen	Cwa	[M] 10y		$\checkmark$			LST	Landsat	City boundary	LC	[C]Landsat	T/G
(Xu et al., 2017)China - BeijingDwa[S] $$ LSTLandsatCentral built-up areaLU[F]QuickBirdT/G(Yan et al., 2019)US - PhoenixBWh[S] $$ LSTMASTERLocal neighborhoodLC[F]NAIPT/G(Yan et al., 2021)China - ChangchunDwa[S] $$ $$ LSTLandsatCentral built-up areaLC[F]SPOTNo(Yang, He, Yu, et al., 2017)China - ChangchunDwa[S] $$ $$ LSTLandsatCentral built-up areaLC[F]GFNo(Yang et al., 2021)China - ChangchunDwa[S] $$ $$ LSTLandsatCentral built-up areaLC[F]GFNo(Yang et al., 2022)China - FuzhouDemark - CopenhagenDfb[S] $$ $$ $$ LSTLandsatCentral built-up areaLC[F]Governmental dataT/G(Yang et al., 2021)Demark - CopenhagenDfb[S] $$ $$ $$ LSTLandsatCentral built-up areaLC[F]Governmental dataT/G(Yang et al., 2022)Demark - CopenhagenDfb[S] $$ $$ LSTLandsatCentral built-up areaLC[F]Governmental dataT/G(L'Ang et al., 2021)China - FuzhouCfa[M]3y $$ $$ LSTLandsatCentral built-up areaLC[F]GFT/G(L'Ang et al., 2021)China - FuzhouCfa <td< td=""><td>(Xie et al., 2013)</td><td>China - Shenzhen</td><td>Cwa</td><td>[S]</td><td></td><td></td><td><math>\checkmark</math></td><td></td><td>LST</td><td>Landsat</td><td>City boundary</td><td>LC</td><td>[C]Landsat</td><td>T/G</td></td<>	(Xie et al., 2013)	China - Shenzhen	Cwa	[S]			$\checkmark$		LST	Landsat	City boundary	LC	[C]Landsat	T/G
(Yan et al., 2019)US - PhoenixBWh[S] $$ LSTMASTERLocal neighborhoodLC[F]NAIPT/G(Yan et al., 2021)China - BeijingDwa[S] $$ $$ LSTLandsatCentral built-up areaLC[F]SPOTNo(Yang, He, Yu, et al., 2017)China - ChangchunDwa[S] $$ $$ $$ LSTLandsatCentral built-up areaLC[F]GFNo(Yang, He, Yu, et al., 2017)China - ChangchunDwa[S] $$ $$ LSTLandsatCentral built-up areaLC[F]GFNo(C. Yang et al., 2021)China - ChangchunDwa[S] $$ $$ $$ LSTLandsat, Field MeasuredCentral built-up areaLC[F]Governmental dataT/G(Yang et al., 2020)Denmark - CopenhagenDfb[S] $$ $$ $$ LSTLandsatCentral built-up areaLC[F]Governmental dataT/G(Yang et al., 2021)Denmark - CopenhagenDfb[S] $$	(Xu et al., 2017)	China - Beijing	Dwa	[S]		$\checkmark$			LST	Landsat	Central built-up area	LU	[F]QuickBird	T/G
(Yan et al., 2021)China - BeijingDwa[S] $$ LSTLandsatCentral built-up areaLC[F]SPOTNo(Yang, He, Wang, et al., 2017)China - ChangehunDwa[S] $$ $$ $$ LSTLandsatCentral built-up areaLC[F]GFNo(Yang, He, Yu, et al., 2017)China - ChangehunDwa[S] $$ $$ $$ LSTLandsatCentral built-up areaLC[F]GFNo(C. Yang et al., 2021)China - ChangehunDfb[S] $$	(Yan et al., 2019)	US - Phoenix	BWh	[S]		$\checkmark$			LST	MASTER	Local neighborhood	LC	[F]NAIP	T/G
(Yang, He, Wang, et al., 2017)China - ChangchunDwa[S] $\sqrt{1}$ $\sqrt{1}$ $\sqrt{1}$ LSTLandsatCentral built-up areaLC[F]GFNo(Yang, He, Yu, et al., 2017)China - ChangchunDwa[S] $\sqrt{1}$ $\sqrt{1}$ $\sqrt{1}$ LSTLandsatCentral built-up areaLU[F]GFT/G(C. Yang et al., 2021)Denmark - CopenhagenDfb[S] $\sqrt{1}$ $\sqrt{1}$ $\sqrt{1}$ $\sqrt{1}$ LSTLandsat, Field MeasuredCentral built-up areaLC[F]Governmental dataT/G(Yang et al., 2020)Denmark - CopenhagenDfb[S] $\sqrt{1}$ $\sqrt{1}$ LSTLandsatCentral built-up areaLC[F]Governmental dataT/G(Yang et al., 2021)China - FuzhouCfa[M]3y $\sqrt{1}$ $\sqrt{1}$ LSTLandsatCentral built-up areaLC[F]GFT/G(L. Yang et al., 2021)China - FuzhouCfa[S] $\sqrt{1}$ $\sqrt{1}$ LSTLandsatCity boundaryLC[F]GFNo	(Yan et al., 2021)	China - Beijing	Dwa	[S]		$\checkmark$			LST	Landsat	Central built-up area	LC	[F]SPOT	No
(Yang, He, Yu, et al., 2017)China - ChangchunDwa[S] $\sqrt{1}$ $\sqrt{1}$ LSTLandsatCentral built-up areaLU[F]GFT/G(C. Yang et al., 2021)China - ChangchunDwa[S] $\sqrt{1}$ $\sqrt{1}$ $\sqrt{1}$ $AT/L_LST$ Central built-up areaLC[F]GFNo(Yang et al., 2022)Denmark - CopenhagenDfb[S] $\sqrt{1}$ $\sqrt{1}$ $\sqrt{1}$ LSTLandsatCentral built-up areaLC[F]Governmental dataT/G(Yang et al., 2021)China - FuzhouCfa[S] $\sqrt{1}$ $\sqrt{1}$ LSTLandsatCentral built-up areaLC[F]GFNo(L. Yang et al., 2021)China - FuzhouCfa[S] $\sqrt{1}$ $\sqrt{1}$ LSTLandsatCity boundaryLC[F]GFNo	(Yang, He, Wang, et al., 2017)	China - Changchun	Dwa	[S]	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	LST	Landsat	Central built-up area	LC	[F]GF	No
(C. Yang et al., 2021)China - ChangchunDwa[S] $$ $AT/$ LSTLandsat, Field MeasuredCentral built-up areaLC[F]GFNo(Yang et al., 2020)Denmark - CopenhagenDfb[S] $\sqrt{$ $\sqrt{$ $\sqrt{$ $\sqrt{$ LSTLandsatCentral built-up areaLC[F]Governmental dataT/G(Yang et al., 2020)China - FuzhouCfa[M]3y $\sqrt{$ $\sqrt{$ $\sqrt{$ LSTLandsatCentral built-up areaLC[F]GFNo(L. Yang et al., 2021)China - FuzhouCfa[S] $\sqrt{$ $\sqrt{$ $\sqrt{$ LSTLandsatCity boundaryLC[F]GFNo	(Yang, He, Yu, et al., 2017)	China - Changchun	Dwa	[S]	$\checkmark$	$\checkmark$	$\checkmark$		LST	Landsat	Central built-up area	LU	[F]GF	T/G
(Yang et al., 2020)Denmark - CopenhagenDfb[S] $\sqrt{1}$ $\sqrt{1}$ LSTLandsatCentral built-up areaLC[F]Governmental dataT/G(Yang et al., 2022)China - FuzhouCfa[M]3y $\sqrt{1}$ LSTLandsatCentral built-up areaLC[F]GFT/G(L. Yang et al., 2021)China - FuzhouCfa[S] $\sqrt{1}$ $\sqrt{1}$ LSTLandsatCity boundaryLC[F]GFNo	(C. Yang et al., 2021)	China - Changchun	Dwa	[S]		$\checkmark$			AT / LST	Landsat, Field Measured	Central built-up area	LC	[F]GF	No
(Yang et al., 2022)China - FuzhouCfa[M]3y $\sqrt$ LSTLandsatCentral built-up areaLC[F]GFT/G(L. Yang et al. 2021)China - FuzhouCfa[S] $\sqrt{\sqrt{1-1}}$ VVLSTLandsatCity boundaryLC[F]GFNo	(Yang et al., 2020)	Denmark - Copenhagen	Dfb	[S]	$\checkmark$	$\checkmark$	$\checkmark$		LST	Landsat	Central built-up area	LC	[F]Governmental data	T/G
(L Yang et al. 2021) China - Fuzhou Cfa [S] $\sqrt{\sqrt{1 ST}}$ Landsat City boundary LC [FIGE No	(Yang et al., 2022)	China - Fuzhou	Cfa	[M]3y					LST	Landsat	Central built-up area	LC	[F]GF	T/G
	(L. Yang et al., 2021)	China - Fuzhou	Cfa	[S]	$\checkmark$				LST	Landsat	City boundary	LC	[F]GF	No
(Yao et al., 2020) China - Beijing Dwa [S] $\sqrt{\sqrt{\sqrt{\sqrt{\sqrt{\sqrt{\sqrt{\sqrt{\sqrt{\sqrt{\sqrt{\sqrt{\sqrt{\sqrt{\sqrt{\sqrt{1/\sqrt{1/$	(Yao et al., 2020)	China - Beijing	Dwa	[S]					LST	Landsat	Central built-up area	LC	[F]IKONOS	No

	Geographic	al range <sup>1</sup>		Tempo	ral range			Temperature indicator			UGS classification and identification		
Citation	Location	Climate zone	Year span	Sp <sup>2</sup>	Su <sup>2</sup>	Au <sup>2</sup>	Wi <sup>2</sup>	Туре	Data Source	Spatial Range <sup>3</sup>	UGS definition	Data Source <sup>4</sup>	Detailed Classification <sup>5</sup>
(Ye et al., 2021)	China-Beijing, Tianjin, Shanghai,Guangzhou, Shenzhen	Dwa, Dwa, Cwa, Cwa	[M]27y		$\checkmark$			LST	Landsat	Central built-up area	LC	[F]IKONOS	No
(Yin et al., 2019)	China - Beijing	Dwa	[S]			$\checkmark$		LST	Landsat	Central built-up area	LC	[F]SPOT	T/G
(Yu et al., 2020)	China - Shanghai	Cfa	[S]		$\checkmark$			LST	Landsat	Central built-up area	LC	[F]ZY-3	No
(Yu et al., 2017)	China - Fuzhou	Cfa	[M] 13y		$\checkmark$			LST	Landsat	Central built-up area	LC	[F]SPOT	T/G
(Yuan et al., 2021)	China - Xi'an	BSk	[S]		$\checkmark$			LST	Landsat	Central built-up area	LC	[F]GF2	T/G
(Zawadzka et al., 2020)	UK - Milton keynes, bedford, luton/dunstable	Cfb	[S]		$\checkmark$			LST	Landsat	Central built-up area	LC	[F]Governmental data	T/G
(Zawadzka et al., 2021)	UK - Milton keynes, bedford, luton/dunstable	Cfb	[S]		$\checkmark$			LST	Landsat	Central built-up area	LC	[F]LiDAR	T/G
(Zeng et al., 2022)	China - Shanghai	Cfa	[S]		$\checkmark$			LST	Landsat	Central built-up area	LC	[F]GF2	T/G
(H. Zhang et al., 2022)	China - Shanghai	Cfa	[M]7y		$\checkmark$			LST	Landsat	Local neighborhood	LC	[F]Governmental data: 1m	T/G
(L. Zhang et al., 2022)	China - Beijing	Dwa	[S]					LST	Landsat	Central built-up area	LC	[F]WorldView	No
(M. Zhang et al., 2022)	China - Urumqi	BWk	[S]		$\checkmark$			LST	Landsat	Central built-up area	LC	[F]GF	No
(Zhang et al., 2009)	China - Nanjing	Cfa	[S]		$\checkmark$			LST	Landsat	Central built-up area	LC	[F]IKONOS	T/S/G
(Y. Zhang et al., 2022)	China - Xuzhou	Cfa	[M]6y	$\checkmark$				LST	Landsat	Central built-up area	LC	[F]GF	No
(Zhao et al., 2020)	China - Zhengzhou	Cwa	[M] 15y					LST	Landsat	City boundary	LC	[C]Landsat	T/G
(W. Zhou et al., 2022)	China - Beijing, Tianjin, Shanghai	Dwa, Dwa, Cfa	[S]		$\checkmark$			LST	Landsat	Central built-up area	LC	[C]Landsat	T/G
(G. Zhou et al., 2019)	US - Washington DC	Cfa	[S]	$\checkmark$				LST	Landsat	City boundary	OC	[C]ASTER	No
(L. Zhou et al., 2022)	China - Xi'an	BSk	[S]		$\checkmark$			LST	Landsat	Metropolitan area	LC	[C]Sentinel	No
(Zhou & Cao, 2020)	China - Shanghai	Cfa	[S]	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	LST	Landsat	Central built-up area	LC	[F]SPOT	T/G
(W. Zhou, F. Cao, et al., 2019)	China - Shanghai	Cfa	[S]		$\checkmark$			LST	Landsat	Central built-up area	LC	[F]SPOT	T/G
(W. Zhou, X. Shen, et al., 2019)	China - Nanjing	Cfa	[S]	$\checkmark$				LST	Landsat	Central built-up area	LC	[C]Landsat	No
(Zhou et al., 2011)	US - Baltimore	Cfa	[S]		$\checkmark$			LST	Landsat	Central built-up area	LC	[F]LiDAR	T/G
(Zhou et al., 2017)	US - Sacramento, Baltimore	Csa, Cfa	[S]					LST	Landsat	City boundary	LC	[F]NAIP	T only
(Zhu et al., 2021)	China - Jinan	Dwa	[M]3y mean		$\checkmark$			LST	Landsat	Central built-up area	LU	[F]GF2	No

Note: 1 Climate zone classified following world's current Köppen climate classification. 2 Sp=spring, Su=summer, Au=autumn, Wi=winter. [M] refers to that multiple years' data were used. [S] refers to that single year data was used. 3 Classified into 4 types, i.e., metropolitan area, city boundary, central built-up area, and local neighborhood, by the spatial range taken into consideration of analysis. 4 [C] Coarse resolution data used, [F] Fine resolution data used. 5 T only=tree canopy specified only, T/G=specified tree canopy and grassland/cropland coverage, T/S/G=specified tree canopy, shrub coverage, and grassland/cropland coverage, DC=detailed classification.





Fig. A1 Reviewed paper amount by (a)country, and (b) Köppen climate zone, (c) published year, and (d) published journals.

(a)



### Appendix B Frequency of landscape metrics used in reviewed papers

#### Table B1 2D patch level LMs used in reviewed papers

Metric	Landscape metric	Calculation <sup>#</sup>	Description <sup>#</sup>	Range	Frequency in reviewed papers
category					
Shape metrics	Perimeter-area ratio (PARA)	$PARA = \frac{p_{ij}}{A_{ij}}$	It describes the patch complexity in a straightforward way. However, because it is not standardized to a certain shape (e.g., a square), it is not scale independent, meaning that increasing the patch size while not changing the patch form will change the ratio.	PARA > 0 Increases, without limit, as the shape complexity increases.	<b>15</b> (Asgarian et al., 2014; Bao et 2018; Huang et al., 2022; V 2016; Vaz Monteiro et al., 2 et al., 2017; Zhang et al., 20
	Shape index (SHAPE)	$SHAPE - \frac{p_{ij}}{p_{ij}}$ (a)	It describes the patch complexity by comparing the	SHAPE≥1	34
		$SHAPE = \frac{p_{ij}}{4\sqrt{A_{ij}}} $ (b)	shape to a circle (a) or a square (b). It corrects the size problems of PARA and offers a simple and straightforward way of describing shape complexity.	Increases, without limit, as the shape complexity increases. SHAPE = 1 when the patch is circle (a) or square (b).	16 papers used equation (a) (Cao et al., 2010; Chen et Park & Cho, 2016; Sh 2013; X. Y. Tan et al., 2 2020; Yu et al., 2017; W
					<ul> <li>(X. Chen et al., 2021; Y. L et al., 2022; Xu et al., Zhou et al., 2022; Zhu</li> <li>7 papers didn't specify (Asgarian et al., 2014; Ca Rodríguez et al., 2022;</li> </ul>
	Fractal dimension index (FRAC)	$FRAC = \frac{2 * \ln (0.25 * p_{ij})}{\ln A_{ij}}$	The index is based on the patch perimeter and the patch area and describes the patch complexity. Because it is standardized, it is scale independent, meaning that increasing the patch size while not changing the patch form will not change the ratio.	1≤FRAC≤2 Approaches FRAC = 1 for a squared patch shape form and FRAC = 2 for an irregular patch shape.	<b>5</b> (Cai et al., 2022; Chen et al., 2 Yu et al., 2017)
Core area metrics	Core area index (CAI)	$CAI = \left(\frac{a_{ij}^{core}}{a_{ij}}\right) * 100$	It equals the percentage of a patch that is core area. A cell is defined as core area if the cell has no neighbor with a different value than itself (rook's case). It describes patch area and shape simultaneously (more core area when the patch is large and the shape is rather compact, i.e., a square). Because the index is relative, it is comparable among patches with different area.	0≤CAI≤100 CAI = 0 when the patch has no core area and approaches CAI = 100 with increasing percentage of core area within a patch.	<b>1</b> (Asgarian et al., 2014)
Self-defined metrics	Mean shape index (MSI)	$MSI = \frac{p_{ij}}{\sqrt{A_{ij}}}$	NA	Increases, without limit, as the shape complexity increases.	(Jaganmohan et al., 2016)
	Mean span (MS)	$MS = \frac{L_w + L_l}{2}$	where $L_w$ is the park width, and $L_l$ is the park length.	NA	(Vaz Monteiro et al., 2016)
	Park vegetation and shape index (PVSI)	$PVSI = log_{10} \left( \frac{A_{tree} + A_{shrub}}{SHAPE} \right)$	where $A_{tree}$ and $A_{shrub}$ refer to the areas of tree and shrub cover (m2). Designed to interpret PCI.	NA	(Cao et al., 2010)
	Length-width ratio	$SI = \frac{L_l}{L_w}$	where $L_w$ is the park width, and $L_l$ is the park length.	NA	(Sun et al., 2021)
			7		

t al., 2016; Du et al., 2021; Ekwe et al., 2020; Huang et al., W. Liu et al., 2022; Qiu & Jia, 2020; Ren et al., 2013; Shih, 2016; Wang et al., 2022; Wang et al., 2018; Yang, He, Wang, 209)

t al., 2014b; Du et al., 2017; Fan et al., 2019; Li et al., 2022; hah et al., 2021; Shih, 2017; X. Sun et al., 2020; Tan & Li, 2021; Yan et al., 2021; Yang, He, Yu, et al., 2017; Yang et al., W. Zhou, X. Shen, et al., 2019)

Li et al., 2021; Wenrui Liu et al., 2022; Lu et al., 2012; Pang 2017; Yang, He, Wang, et al., 2017; Zhang et al., 2009; W. et al., 2021)

ai et al., 2022; Feyisa et al., 2014; Gao et al., 2022; Lemoine-; Pramanik & Punia, 2019; W. Zhou, F. Cao, et al., 2019)

2014b; Fan et al., 2019; Pang et al., 2022; Wang et al., 2022;

Self-defined	shape $SI = \frac{A_{ij}}{2}$	NA	SI > 0	(Peng et al., 2021)*
factor	$3I = \frac{1}{p_{ij}}$		Increases, without limit, as the	
			shape complexity decreases.	

\* Confirmed by personal correspondence with the corresponding authors.

# Calculation formulas and descriptions are adopted from McGarigal et al. (2012) and <a href="https://r-spatialecology.github.io/landscapemetrics/index.html">https://r-spatialecology.github.io/landscapemetrics/index.html</a> (accessed Oct. 2022). A area, p perimeter.

#### Table B2 2D class level LMs used in reviewed papers

Metric category	Landscape metric	Calculation <sup>#</sup>	Description	Range	Frequency in reviewed p
Metric category Area and edge metrics	Landscape metric Largest patch index (LPI)	$Calculation^{\#}$ $LPI = \frac{max_{j=1}^{n}(a_{ij})}{A} * 100$	Description It is the percentage of the landscape covered by the corresponding largest patch of each class i. It is a simple measure of dominance.	Range 0 < LPI <= 100 Approaches LPI = 0 when the largest patch is becoming small and equals LPI = 100 when only one patch is present	Frequency in reviewed p 51 (Amani-Beni et al., 2019 2022; J. Chen, P. Du, e al., 2021; Cheng et al. Guo et al., 2020; Guo et al., 2021; Karunarat al., 2020; Li et al., 201 2022; Liu et al., 2018 2021; Masoudi & Tan al., 2014; Shaker et al et al., 2021; Wesley & 2022; Xie et al., 2020; 2022; L. Zhang et al., Zhou et al., 2022; Zho
	Total edge (TE)	TE = E	It measures the configuration of the landscape because a highly fragmented landscape will have many edges. However, total edge is an absolute measure, making comparisons among landscapes with different total areas difficult.	TE >= 0 Equals TE = 0 if all cells are edge cells. Increases, without limit, as landscape becomes more fragmented	al., 2011; Zhou et al., 2 (Liu et al., 2018a; M. Zha
	Edge density (ED)	$ED = \frac{\sum_{k=1}^{m} e_{ik}}{A} * 10000$	It describes the configuration of the landscape, e.g. because an aggregation of the same class will result in a low edge density. The metric is standardized to the total landscape area, and therefore comparisons among landscapes with different total areas are possible.	ED >= 0 Equals ED = 0 if only one patch is present (and the landscape boundary is not included) and increases, without limit, as the landscapes becomes more patchy	<b>59</b> (An et al., 2022; J. Chen, et al., 2022; J. Chen et Dugord et al., 2014; F al., 2020; Guo et al., 2 Huang & Wang, 2019 al., 2020; Li et al., 201 et al., 2012; Liu et al., 2023; Maimaitiyiming 2019; Naeem et al., 202 2021; Shi & Zhao, 202 2022; Wang et al., 202 Brunsell, 2019; Wu et al., 2019; C. Yang et al 2021; Yu et al., 2020; 2020; G. Zhou et al., 2 al., 2017)

a); Athukorala & Murayama, 2020, 2021; D. Chen et al., et al., 2022; J. Chen, W. Zhan, et al., 2022; J. Chen et ..., 2015; Feng & Myint, 2016; Gage & Cooper, 2017; G. et al., 2019; He et al., 2021; Hou & Estoque, 2020; Hu atne et al., 2022; Kong, Yin, James, et al., 2014; B. Li et 18; Liu et al., 2021; K. Liu et al., 2022; S. Liu et al., a, 2018b; Lu et al., 2020; Ma & Peng, 2022; Ma et al., a, 2019; Masoudi et al., 2019; Qian et al., 2018; Ren et al., 2019; Song et al., 2020; Wang et al., 2020; X. Wang & A. Brunsell, 2019; Q. Wu et al., 2021; H. Zhang et al., 2022; M. Zhang et al., 2022; Y. Zhang et al., 2022; L. ou & Cao, 2020; W. Zhou, F. Cao, et al., 2019; Zhou et 2017; W. Zhou et al., 2022)

ang et al., 2022)

a, P. Du, et al., 2022; Chen et al., 2020; J. Chen, W. Zhan, et al., 2021; Cheng et al., 2015; Connors et al., 2012;
Feng & Myint, 2016; Gage & Cooper, 2017; G. Guo et 2021; Guo et al., 2019; He et al., 2021; Hu et al., 2021;
b; Kamarianakis et al., 2017; Kowe et al., 2021; B. Li et 011; T. Li et al., 2021; Li et al., 2017; Li et al., 2013; Li et al., 2016; Liu et al., 2018a; Lu et al., 2020; Lyu et al., 2016; Liu et al., 2018; Qian et al., 2019; Masoudi et al., 2018; Peng et al., 2018; Qian et al., 2018; Rakoto et al., 202; Song et al., 2020; Terfa et al., 2020; Wang & Zhou, 23; X. Wang et al., 2021; Wen et al., 2011; Wesley & A. t al., 2021; L. Yang et al., 2021; Yao et al., 2020; Ye et al., 2021; L. Yang et al., 2021; Yao et al., 2020; Ye et al., 2019; L. Zhou et al., 2022; Zhou et al., 2011; Zhou et al., 2022; Chou et al., 2011; Zhou et al., 2020; Chou et al., 20

Metric category	Landscape metric	Calculation <sup>#</sup>	Description	Range	Frequency in reviewed
	Patch area	AREA_MN	The metric summarizes each class as the	$\geq 0$	56
	distribution	$= mean(AREA[patch_{ij}])$	mean / area weighted mean / standard	AREA_MN/AM=0 if all patches are small.	AREA_MN
	(AREA_)	AREA_AM	deviation / coefficient of variation of all	$AREA_SD/CV = 0$ if all patches are identical in	(Athukorala & Muray
		$= am(AREA[patch_{ij}])$	patch areas belonging to class i.	size.	Zhan, et al., 2022;
		AREA_SD			2016; Gage & Coo
		$= sd(AREA[patch_{ij}])$			al., 2021; Hou & E
		AREA_CV			Ke et al., 2021; Kii
		$= cv(AREA[patch_{ij}])$			al., 2021; Li et al.,
		- /-			Liu et al., 2022; S.
					Ma & Peng, 2022;
					2019; Qian et al., 2
					et al., 2019; Song e
					et al., 2023; Wang
					Yang et al., 2021; Y
					L. Zhang et al., 202
					Cao, 2020; W. Zho
					2017; W. Zhou et a
					AREA AM
					(Liu et al., 2018a, 20)
					Masoudi et al., 201
					AREA SD
					(Feng & Myint, 2016
					AREA CV
					(Li et al., 2019)
					AREA MD
					(M. Zhang et al., 202
	Radius of gyration	GYRATE_MN	The metric summarizes each class as the	$\geq 0$	5
	distribution	$= mean(GYRATE[patch_{ii}])$	mean / area weighted mean of the radius	= 0 if every patch is a single cell. Increases, without	GYRATE MN, GYRAT
	(GYRATE)	GYRATE_AM	of gyration of all patches belonging to	limit, when only one patch is present.	(Gage & Cooper, 201
	· _	$= am(GYRATE[patch_{ii}])$	class i. GYRATE measures the distance		2018b; M. Zhang et al
		where,	from each cell to the patch centroid and		_
		Z,	is based on cell center-to-cell center		
		$GYRATE = \sum \frac{h_{ijr}}{\sum n_{ijr}}$	distances. The metrics characterizes		
		$\sum_{r=1}^{Z} Z$	both the patch area and compactness.		

ayama, 2020, 2021; Chakraborti et al., 2019; J. Chen, W.
by Cheng et al., 2015; Estoque et al., 2017; Feng & Myint, oper, 2017; G. Guo et al., 2020; Guo et al., 2019; He et Estoque, 2020; Hu et al., 2021; Karunaratne et al., 2022; im et al., 2016; Kong, Yin, James, et al., 2014; Kowe et al., 2013; Li et al., 2012; Li et al., 2019; Liu et al., 2021; K.
c. Liu et al., 2022; Liu et al., 2018a, 2018b; Lu et al., 2020; Ma et al., 2021; Masoudi & Tan, 2019; Masoudi et al., 2018; Rakoto et al., 2021; Rouhi et al., 2018; Simwanda et al., 2020; Tang et al., 2022; Wu & Zhang, 2018; L.
Ye et al., 2021; Yuan et al., 2021; H. Zhang et al., 2022; Mou & ou, F. Cao, et al., 2019; Zhou et al., 2011; Zhou et al., al., 2022)

118b; Masoudi & Tan, 2019; Masoudi et al., 2021;19; Shaker et al., 2019; M. Zhang et al., 2022)

6; Qian et al., 2018; Ye et al., 2021; Zhou et al., 2011)

22)

ΓE\_AM 117; Kong, Yin, James, et al., 2014; Liu et al., 2018a, Il., 2022)

Metric category	Landscape metric	Calculation <sup>#</sup>	Description	Range	Frequency in reviewed
Shape metrics	Perimeter-area fractal dimension (PAFRAC)	$PAFRARC = \frac{2}{\beta}$ where $\beta$ is the slope of the regression of the area against the perimeter (logarithm) $n_i \sum_{j=1}^{n} \ln a_{ij}$ $= a + \beta n_i \sum_{j=1}^{n} \ln p_{ij}$	It describes the patch complexity of class i while being scale independent. This means that increasing the patch size while not changing the patch form will not change the metric. However, it is only meaningful if the relationship between the area and perimeter is linear on a logarithmic scale. Furthermore, if there are less than 10 patches in class i, the metric returns NA because of the small-sample issue.	1 <= PAFRAC <= 2 Approaches PAFRAC = 1 for patches with simple shapes and approaches PAFRAC = 2 for irregular shapes	<b>2</b> (Y. Wang et al., 2021)
	Perimeter-area ratio distribution (PARA_)	$PARA_MN = mean(PARA[patch_{ij}])$ $PARA_AM = am(PARA[patch_{ij}])$	It summarizes each class as the mean / area weighted mean of each patch belonging to class i. The perimeter-area ratio describes the patch complexity in a straightforward way.	>0 Increases, without limit, as PARA increases, i.e. patches become more complex.	7 PARA_AM (Kong, Yin, James, e et al., 2022; Zhou & O PARA_MN (Song et al., 2020) Not specified (B. Li et al., 2020) Special use (Peng et al., 2016)
	Shape index distribution (SHAPE_)	SHAPE_MN = mean(SHAPE[patch <sub>ij</sub> ]) SHAPE_AM = am(SHAPE[patch <sub>ij</sub> ]) SHAPE_SD = sd(SHAPE[patch <sub>ij</sub> ])	Each class is summarized as the mean / area weighted mean / standard deviation of each patch belonging to class i.	<ul> <li>SHAPE_MN/AM = 0 if all patches are squares. Increases, without limit, as the shapes of patches become more complex.</li> <li>SHAPE_SD = 0 if all patches have an identical shape index. Increases, without limit, as the variation of the shape index increases.</li> </ul>	48 SHAPE_MN (Athukorala & Mura 2020; J. Chen, W. 2017; Hou & Estor James, et al., 2014 2018a; Lu et al., 2014 2018a; Lu et al., 2018; H 2019; Song et al., 2 Brunsell, 2019; Y. Zhang et al., 2022; 2020; W. Zhou, F. SHAPE_AM (Galletti et al., 2019; Liu et al., 2019; Liu et al., 2018a; N 2021; Masoudi et a al., 2023) SHAPE_SD (Wesley & A. Brunse Different use (X. Chen et al., 2022) Not specified

et al., 2014; Liu et al., 2021; Song et al., 2020; M. Zhang Cao, 2020)

rayama, 2020; J. Chen, P. Du, et al., 2022; Chen et al.,
Zhan, et al., 2022; J. Chen et al., 2021; Estoque et al.,
oque, 2020; Hu et al., 2021; Kim et al., 2016; Kong, Yin,
4; Li et al., 2013; Li et al., 2012; Li et al., 2019; Liu et al.,
2020; Lyu et al., 2023; Ma et al., 2021; Peng et al., 2018;
Rakoto et al., 2021; Rouhi et al., 2018; Simwanda et al.,
2020; Wang et al., 2023; Wang et al., 2020; Wesley & A.
7. Wu et al., 2022; L. Yang et al., 2021; Ye et al., 2021; M.
2; Zhao et al., 2020; L. Zhou et al., 2022; Zhou & Cao,
7. Cao, et al., 2019; Zhou et al., 2011; Zhou et al., 2017)

9; Ke et al., 2021; Kowe et al., 2021; Y. Li et al., 2020; Ma & Peng, 2022; Masoudi & Tan, 2019; Masoudi et al., al., 2019; Shaker et al., 2019; Song et al., 2020; Tang et

sell, 2019; Ye et al., 2021; Zhou et al., 2011)

(B. Li et al., 2020; Wu & Zhang, 2018)

Metric category	Landscape metric	Calculation <sup>#</sup>	Description	Range	Frequency in reviewed
	Fractal index	FRAC_AM	The metric summarizes each class as the	1≤FRAC_MN≤2	22
	distribution	$= am(FRAC[patch_{ij}])$	mean / area weighted mean of the	Approaches 1 for a squared patch shape form and 2	FRAC_MN
	(FRAC_)	FRAC_MN	fractal dimension index of all patches	for an irregular patch shape.	(Liu et al., 2018a, 20
		$= mean(FRAC[patch_{ij}])$	belonging to class i.		2020; M. Zhang et al.
					FRAC_AM
					(An et al., 2022; Cor
					2019; Kowe et al.
					Masoudi et al., 20
					2021; Wen et al., 2
					Not specified
					(Dugord et al., 2014
	Related	CIRCLE_AM	It summarizes each class as the mean / area	>0	4
	circumscribing	$= am(CIRCLE[patch_{ii}])$	weighted mean of the related	= 0 if the related circumscribing circle of all patches	CIRCLE AM
	circle	CIRCLE_MN	circumscribing circle of all patches	is small. Increases as the related circumscribing	(Bartesaghi-Koc et al.,
	distribution	$= mean(CIRCLE[patch_{ij}])$	belonging to class i.	circles increase.	CIRCLE MN
	(CIRCLE_)	where,			(Guo et al., 2021; Liu e
		$CIRCLE = 1 - \frac{a_{ij}}{a_{ij}^{circle}}$			
	Contiguity index	CONTIG_AM	It summarizes each class as the mean of	0≤CONTIG≤1	7
	distribution	$= am(CONTIG[patch_{ij}])$	each patch belonging to class i. It	Equals 0 for one-pixel patches and increases to a	CONTIG_AM
	(CONTIG_)	CONTIG_MN	assesses the spatial connectedness	limit of 1 (fully connected patch).	(Galletti et al., 2019; G
		$= mean(CONTIG[patch_{ij}])$	(contiguity) of cells in patches.		Zhang et al., 2022)
		where,			CONTIG_MN
		$\left[\sum_{r=1}^{Z} c_{ijr}\right]$			(Chakraborti et al., 201
		$\begin{bmatrix} \frac{a_{ij}}{a_{ij}} \end{bmatrix} = 1$			Not specified
		$conner = \frac{v-1}{v-1}$			(Dugord et al., 2014)
Aggregation	Interspersion and	IJI	It describes the intermixing of classes (i.e.	0 < IJI <= 100	8
metrics	juxtaposition	$\sum_{m} \left[ \left( \underbrace{e_{ik}}{e_{ik}} \right)_{ln} \left( \underbrace{e_{ik}}{e_{ik}} \right)_{ln} \right] \right]$	without considering like adjacencies -	Approaches 0 if a class is only adjacent to a single	(An et al., 2022; Chakr
	index (IJI)	$=\frac{-\sum_{k=1}^{m}\left[\left(\sum_{k=1}^{m}e_{ik}\right)^{m}\left(\sum_{k=1}^{m}e_{ik}\right)^{m}\right]}{\sum_{k=1}^{m}e_{ik}}$	the diagonal of the adjacency table).	other class and equals 100 when a class is	2017; Galletti et al., 201
		$\ln(m-1)$	The number of classes to calculate IJI	equally adjacent to all other classes.	2022)
		* 100	must be $\geq=$ than 3.		
	Percentage of like	$PIADI - \left( \frac{g_{ij}}{2} \right) * 100$	It calculates the frequency how often	0 <= PLADJ <= 100	8
	adjacencies	$\sum_{k=1}^{m} g_{ik} + 100$	patches of different classes i (focal	Equals $PLADJ = 0$ if class i is maximal	(D. Chen et al., 2022; D
	(PLADJ)		class) and k are next to each other, and	disaggregated, i.e. every cell is a different patch.	Song et al., 2020; Wesle
			following is a measure of class	Equals $PLADJ = 100$ when the only one patch is	et al., 2022)
			aggregation. The adjacencies are	present.	
			counted using the double-count method.		

018b; Lyu et al., 2023; Simwanda et al., 2019; Song et al., l., 2022; Zhao et al., 2020)

onnors et al., 2012; Feng & Myint, 2016; Galletti et al., ., 2021; Liu et al., 2018a, 2018b; Masoudi & Tan, 2019; 019; Shaker et al., 2019; Song et al., 2020; X. Wang et al., 2011; Xie et al., 2020; L. Zhang et al., 2022)

4; Kamarianakis et al., 2017; Li et al., 2017)

, 2020; Liu et al., 2018a; M. Zhang et al., 2022)

et al., 2018a)

Guo et al., 2021; Liu et al., 2018a; Song et al., 2020; M.

19; Liu et al., 2018a; Song et al., 2020)

raborti et al., 2019; Feng & Myint, 2016; Gage & Cooper, 19; B. Li et al., 2020; Song et al., 2020; M. Zhang et al.,

Dugord et al., 2014; Lyu et al., 2023; Shaker et al., 2019; ey & A. Brunsell, 2019; Zawadzka et al., 2021; M. Zhang

Metric category	Landscape metric	Calculation <sup>#</sup>	Description	Range	Frequency in reviewed
	Aggregation index (AI)	$AI = \left[\frac{g_{ii}}{max - g_{ii}}\right] (100)$	It equals the number of like adjacencies divided by the theoretical maximum possible number of like adjacencies for that class. The metric is based on he adjacency matrix and the the single- count method.	0 <= AI <= 100 Equals 0 for maximally disaggregated and 100 for maximally aggregated classes.	<b>39</b> (Amani-Beni et al., 2014 D. Chen et al., 2022; Esta 2020; Kong, Yin, James, al., 2022; Liu et al., 2018 2022; Ma et al., 2021; M 2014; Shaker et al., 2019 2020; X. Wang et al., 202 2018; Xie et al., 2020; L. Zhang et al., 2022; M. Zh 2022; Zhou & Cao, 2020
	Clumpiness index (CLUMPY)	$Give G_{i} = \left(\frac{g_{ii}}{\sum_{k=1}^{m} g_{ik}}\right)$ $CLUMPY$ $= \left  \frac{\frac{G_{i} - P_{i}}{1 - P_{i}} \text{ for } G_{i} \ge P_{i}}{\frac{G_{i} - P_{i}}{1 - P_{i}} \text{ for } G_{i} < P_{i}, P_{i} \ge 0.3}{\frac{G_{i} - P_{i}}{-P_{i}} \text{ for } G_{i} < P_{i}, P_{i} < 0.3} \right $	It equals the proportional deviation of the proportion of like adjacencies involving the corresponding class from that expected under a spatially random distribution. The metric is based on the adjacency matrix and the the double- count method.	<ul> <li>-1 &lt;= CLUMPY &lt;= 1</li> <li>Equals -1 for maximally disaggregated, 0 for randomly distributed and 1 for maximally aggregated classes.</li> </ul>	9 (Gage & Cooper, 2017; Shaker et al., 2019; Song Zhou et al., 2019)
	Landscape shape index (LSI)	$LSI = \frac{p_{ij}}{\min p_{ij}}$	LSI is an 'Aggregation metric'. It is the ratio between the actual edge length of class i and the hypothetical minimum edge length of class i. The minimum edge length equals the edge length if class i would be maximally aggregated.	LSI >= 1 Increases, without limit, as the length of the actual edges increases, i.e. the patches become less compact.	44 (Amani-Beni et al., 2019 et al., 2015; Connors et al. & Wang, 2019; Kamarian al., 2020; T. Li et al., 2022 & Q. Weng, 2009; Liu et & Peng, 2022; Masoudi & Peng et al., 2018; Rakoto et al., 2020; Tang et al., 20 al., 2021; Wu et al., 2014 2021; H. Zhang et al., 20 Zhang et al., 2022; Zhao
	Normalized landscape shape index (nLSI)	$nLSI = \frac{e_i - \min e_i}{\max e_i - \min e_i}$	It describes the ratio of the actual edge length of class i in relation to the hypothetical range of possible edge lengths of class i (min/max). It ignores all background cells when calculating the minimum and maximum total edge length.	0 <= nlsi <= 1 Equals nLSI = 0 when only one squared patch is present. nLSI increases the more disaggregated patches are and equals nLSI = 1 for a maximal disaggregated (i.e. a "checkerboard pattern").	4 (Bartesaghi-Koc et al., 2 et al., 2022)

#### papers

19; An et al., 2022; Athukorala & Murayama, 2020, 2021; toque et al., 2017; Feng et al., 2020; Hou & Estoque, s, et al., 2014; B. Li et al., 2020; Liu et al., 2021; S. Liu et 8a, 2018b; Lu et al., 2020; Lyu et al., 2023; Ma & Peng, *M*asoudi & Tan, 2019; Masoudi et al., 2019; Ren et al., 9; Simwanda et al., 2019; Song et al., 2020; Wang et al., 021; Wu et al., 2021; Y. Wu et al., 2022; Wu & Zhang, L. Yang et al., 2021; Y. Zhang et al., 2022; L. Zhou et al., 0; W. Zhou, F. Cao, et al., 2019)

B. Li et al., 2020; Li et al., 2011; Liu et al., 2018a; g et al., 2020; Wu et al., 2021; M. Zhang et al., 2022; G.

19; Chakraborti et al., 2019; D. Chen et al., 2022; Cheng al., 2012; Gage & Cooper, 2017; Guo et al., 2021; Huang anakis et al., 2017; Li et al., 2018; Li et al., 2011; T. Li et 21; Li et al., 2017; Li et al., 2013; Li et al., 2012; H. Liu et al., 2016; Liu et al., 2018a, 2018b; Lyu et al., 2023; Ma & Tan, 2019; Masoudi et al., 2019; Naeem et al., 2018; to et al., 2021; Ren et al., 2014; Shi & Zhao, 2022; Song 2023; Wang & Zhou, 2022; X. Wang et al., 2021; Wu et 4; Yan et al., 2019; Yin et al., 2019; Zawadzka et al., 022; L. Zhang et al., 2022; M. Zhang et al., 2022; Y. b et al., 2020)

2020; Gage & Cooper, 2017; Liu et al., 2018a; M. Zhang

Metric category	Landscape metric	Calculation <sup>#</sup>	Description	Range	Frequency in reviewed
	Patch cohesion index (COHESION)	$COHESION = 1 - \left(\frac{\sum_{j=1}^{n} p_{ij}}{\sum_{j=1}^{n} p_{ij} \sqrt{a_{ij}}}\right) \\ * \left(1 - \frac{1}{\sqrt{Z}}\right)^{-1} * 100$	It characterizes the connectedness of patches belonging to class i. It can be used to assess if patches of the same class are located aggregated or rather isolated and thereby COHESION gives information about the configuration of the landscape.	0 < COHESION < 100 Approaches COHESION = 0 if patches of class i become more isolated. Increases if patches of class i become more aggregated.	<b>29</b> (D. Chen et al., 2022; J. al., 2021; Feng et al., 202 Karunaratne et al., 2022; Liu et al., 2018a; Ma & F al., 2020; Sun et al., 2022; al., 2021; Yu et al., 2020; et al., 2022; Zhou & Cao
	Number of patches (NP)	$NP = n_i$	It describes the fragmentation of a class, however, does not necessarily contain information about the configuration or composition of the class.	NP >= 1 Equals NP = 1 when only one patch is present and increases, without limit, as the number of patches increases	<b>15</b> (Amani-Beni et al., 2019; Karunaratne et al., 2022; Masoudi & Tan, 2019; M 2022; Yin et al., 2019; L. Cao, et al., 2019; W. Zho
	Patch density (PD)	$PD = \frac{n_i}{A} * 10000 * 100$	It describes the fragmentation of a class, however, does not necessarily contain information about the configuration or composition of the class.	PD > 0 Increases as the landscape gets more patchy. Reaches its maximum if every cell is a different patch.	66 (Amani-Beni et al., 2019 P. Du, et al., 2022; Chen Connors et al., 2012; Dug 2019; Guo et al., 2021; H al., 2021; Kong, Yin, Jan al., 2021; Kong, Yin, Jan al., 2017; Li et al., 2013; H. Liu & Q. H. Weng, 20 Liu et al., 2018a, 2018b; al., 2014; Masoudi & Tar Naeem et al., 2018; Peng et al., 2021; Ren et al., 202 2021; Y. Wang et al., 202 al., 2014; Xie et al., 2020 2021; Yao et al., 2020; Ya al., 2021; M. Zhang et al., & Cao, 2020; Zhou et al.
	Landscape division index (DIVISION)	DIVISION $= \left(1 - \sum_{j=1}^{n} \left(\frac{a_{ij}}{A}\right)^{2}\right)$	It can be in as the probability that two randomly selected cells are not located in the same patch of class i. The landscape division index is negatively correlated with the effective mesh size (MESH).	0 <= Division < 1 Equals DIVISION = 0 if only one patch is present. Approaches DIVISION = 1 if all patches of class i are single cells.	12 (D. Chen et al., 2022; Fe et al., 2018a, 2018b; Shal Q. Wu et al., 2022; M. Zh
	Splitting index (SPLIT)	$SPLIT = \frac{A^2}{\sum_{j=1}^n a_{ij}^2}$	It describes the number of patches if all patches of class i would be divided into equally sized patches.	<ul> <li>1 &lt;= SPLIT &lt;= Number of cells squared</li> <li>Equals SPLIT = 1 if only one patch is present.</li> <li>Increases as the number of patches of class i</li> <li>increases and is limited if all cells are a patch</li> </ul>	<b>9</b> (D. Chen et al., 2022; B Zhao, 2022; Sun et al., 20 Zhang et al., 2022)

#### papers

. Chen, P. Du, et al., 2022; Chen et al., 2020; J. Chen et 20; Gage & Cooper, 2017; Huang & Wang, 2019; Kim et al., 2016; Kowe et al., 2021; B. Li et al., 2020; Peng, 2022; Ren et al., 2014; Shaker et al., 2019; Song et 2; Wesley & A. Brunsell, 2019; Q. Wu et al., 2022; Ye et ; Zawadzka et al., 2021; M. Zhang et al., 2022; Y. Zhang o, 2020; Zhou et al., 2011)

9; D. Chen et al., 2022; Gage & Cooper, 2017;
; Kim et al., 2016; Kong, Yin, James, et al., 2014;
! Aasoudi et al., 2019; Song et al., 2020; Q. Wu et al.,
. Zhang et al., 2022; M. Zhang et al., 2022; W. Zhou, F. ou et al., 2022)

9; Chakraborti et al., 2019; D. Chen et al., 2022; J. Chen, et al., 2020; J. Chen et al., 2021; Cheng et al., 2015; gord et al., 2014; Gage & Cooper, 2017; Galletti et al., Juang & Wang, 2019; Kamarianakis et al., 2017; Ke et nes, et al., 2014; B. Li et al., 2020; Li et al., 2011; Li et Li et al., 2012; Li et al., 2019; H. Liu & Q. Weng, 2009; 009; Liu et al., 2021; K. Liu et al., 2022; Liu et al., 2016; Lyu et al., 2023; Ma & Peng, 2022; Maimaitiyiming et n, 2019; Masoudi et al., 2021; Masoudi et al., 2019; g et al., 2018; Peng et al., 2016; Qian et al., 2018; Rakoto 014; Shaker et al., 2019; Shi & Zhao, 2022; Simwanda et 20; Tang et al., 2023; Terfa et al., 2020; X. Wang et al., 21; Wesley & A. Brunsell, 2019; Wu et al., 2021; Wu et ); Yan et al., 2019; C. Yang et al., 2021; L. Yang et al., Ye et al., 2021; Yin et al., 2019; Yu et al., 2020; Yuan et ., 2022; G. Zhou et al., 2019; L. Zhou et al., 2022; Zhou , 2011)

eng et al., 2020; B. Li et al., 2020; T. Li et al., 2021; Liu ker et al., 2019; Song et al., 2020; Y. Wang et al., 2021; hang et al., 2022; Zhao et al., 2020)

3. Li et al., 2020; Liu et al., 2018a; Ren et al., 2014; Shi & 022; X. Wang et al., 2021; H. Zhang et al., 2022; M.

Metric category	Landscape metric	Calculation <sup>#</sup>	Description	Range	Frequency in reviewed p
	Effective mesh size (MESH)	$MESH = \frac{\sum_{j=1}^{n} a_{ij}^2}{A} * \frac{1}{10000}$	Because each patch is squared before the sums for each group i are calculated and the sum is standardized by the total landscape area, MESH is a relative measure of patch structure.	cell size / total area <= MESH <= total area Equals cell size/total area if class covers only one cell and equals total area if only one patch is present.	5 (D. Chen et al., 2022; Lin M. Zhang et al., 2022)
	Euclidean nearest neighbor distance distribution (ENN_)	$ENN\_AM$ = $am(ENN[patch_{ij}])$ $ENN\_MN$ = $mean(ENN[patch_{ij}])$ $ENN\_SD$ = $sd(ENN[patch_{ij}])$ where, $ENN = h_{ij}$	It summarizes each class as the mean / area weighted mean / standard deviation of each patch belonging to class i.	ENN_MN/_AM> 0 = 0 as the distance to the nearest neighbor decreases, i.e. patches of the same class i are more aggregated. ENN_SD > 0 = 0 if the nearest-neighbor distance is identical for all patches.	19 ENN_MN (Cheng et al., 2015; Ke e 2012; Li et al., 2019; Mas 2021; Rouhi et al., 2018; 7 Ye et al., 2021; Yu et al., 2 ENN_AM (Masoudi & Tan, 2019; I al., 2022) ENN_SD (Ye et al., 2021; Zhou et
	Proximity index distribution (PROX_)	$PROX\_AM$ = am(PROX[patch <sub>ij</sub> ]) PROX_MN = mean(PROX[patch <sub>ij</sub> ]) where, $PROX = \sum_{s=1}^{n} \frac{a_{ijs}}{h_{ijs}^{2}}$	It summarizes each class as the mean / area weighted mean of each patch belonging to class i.	<ul> <li>PROX_≥0</li> <li>= 0 if all patches of the corresponding patch type have no neighbors of the same type within the specified search radius. It increases as patches of the corresponding patch type become less isolated and the patch type becomes less fragmented in distribution.</li> </ul>	4 PROX_MN (Feng & Myint, 2016; La PROX_AM (Shaker et al., 2019) Not specified (Yu et al., 2020)
	Connectance (CONNECT)	$CONNECT = \left[\frac{\sum_{j \neq k}^{n} c_{ijk}}{\frac{n_i(n_i - 1)}{2}}\right]$	It equals the number of functional joinings between all patches of the corresponding patch type, divided by the number of possible joinings.	0 <connect≤100 =0 when either the focal class consists of a single patch or none of the patches of the focal class are connected. =100 when every patch of the focal class is connected</connect≤100 	<b>2</b> (Amani-Beni et al., 2019
Core area metrics	Core area distribution (CORE_)	$CORE\_AM$ = $am(CORE[patch_{ij}])$ where, $CORE = n_{ij}^{core}$	The metric summarizes each class as the area weighted mean of the core area of all patches belonging to class i.	<pre>CORE_AM ≥0 = 0 if CORE = 0 for all patches. Increases, without limit, as the core area indices increase.</pre>	1 CORE_AM (Shaker et al., 2019)
	Core area index distribution (CAI_)	CAI_AM = am(CAI[patch <sub>ij</sub> ]) CAI_MN = mean(CAI[patch <sub>ij</sub> ])	The metric summarizes each class as the mean / area weighted mean of the core area index of all patches belonging to class i.	0≤CAI_MN/AM≤100 = 0 when all patches have no core area, and = 100 with increasing percentage of core area within patches.	<b>1</b> CAI_AM (Shaker et al., 2019)

#### papers

iu et al., 2018a; Shaker et al., 2019; Q. Wu et al., 2022;

e et al., 2021; Kim et al., 2016; Li et al., 2013; Li et al., asoudi & Tan, 2019; Masoudi et al., 2019; Rakoto et al., ; Terfa et al., 2020; Wu et al., 2021; Q. Wu et al., 2022; , 2020; M. Zhang et al., 2022; Zhou et al., 2011)

Masoudi et al., 2021; Masoudi et al., 2019; L. Zhang et

t al., 2011)

Li et al., 2019)

9; Shaker et al., 2019)

Metric category	Landscape metric	Calculation <sup>#</sup>	Description	Range	Frequency in reviewed
Contrast metrics	Contrast-weighted	$\sum_{k=1}^{m} (e_{ik} \times d_{ik})$	It equals the sum of lengths of each edge	CWED ≥0	1
	edge density	$CWED = \frac{A}{A}$	segment involving the corresponding	=0 when there is no class edge in the landscape. It	(Du et al., 2016)
	(CWED)		patch type multiplied by the	increases as the amount of class edge in the	
			corresponding contrast weight, divided	landscape increases and / or as the contrast in	
			by the sum of the lengths of all edge	edges involving the corresponding patch type	
			segments involving the same type.	increase.	
Others	FD	ED - n	It measures the fragmentation of patches of	FD>0	1
		$FD = \frac{1}{A_i}$	the same class.	It increases as the patch type is increasingly	(Wu & Zhang, 2018)
				fragmented.	

\* Confirmed by personal correspondence with the corresponding authors.

# Calculation formulas are

#### l papers

#### Table **B3** 2D landscape level LMs used in reviewed papers

Metric category	Landscape metric	Calculation <sup>#</sup>	Description	Range	Fr
Area and edge metrics	Largest patch index	$IDI = \max_{ij} a_{ij} + 100$	It is the percentage of the landscape covered by the	0 < LPI <= 100	10
	(LPI)	$LPI = \frac{1}{A} * 100$	largest patch in the landscape. It is a simple	Approaches $LPI = 0$ when the largest patch is becoming	(0
			measure of dominance.	small and equals $LPI = 100$ when only one patch is present	Сс
					et
					20
	Total edge (TE)	$\sum_{k=1}^{m}$	Total edge includes all edges. It measures the	$TE \ge 0$	1
		$TE = \sum e_{ik}$	configuration of the landscape because a highly	Equals $TE = 0$ if all cells are edge cells. Increases, without	()
		k=1	fragmented landscape will have many edges.	limit, as landscape becomes more fragmented	
			However, total edge is an absolute measure,		
			making comparisons among landscapes with		
	Edge density (ED)	Г	The edge density equals all edges in the landsome	ED > 0	0
	Edge density (ED)	$ED = \frac{E}{A} * 10000$	in relation to the landscape area. The metric	$ED \ge 0$ Equals $ED = 0$ if only one patch is present (and the	0 (1
		A	describes the configuration of the landscape $\alpha$	landscape boundary is not included) and increases without	et
			because an overall aggregation of classes will	limit, as the landscapes becomes more patchy	et
			result in a low edge density. The metric is	······	
			standardized to the total landscape area, and		
			therefore comparisons among landscapes with		
			different total areas are possible.		
	Patch area distribution	AREA_MN	The metric summarizes the total landscape as the	$\geq 0$	7
	(AREA_)	$= mean(AREA[patch_{ij}])$	mean / area weighted mean / standard deviation /	AREA_MN/AM=0 if all patches are small.	AI
		AREA_AM	coefficient of variation of all patch areas belonging	$AREA\_SD/CV = 0$ if all patches are identical in size.	(
		$= am(AREA[patch_{ij}])$	to class i.		Ra
		AREA_SD			AI
		$= sa(AREA[patch_{ij}])$			()
		$AREA_UV$			AI
		$= cv(AKEA[putch_{ij}])$			
					C C
	Radius of gyration	GYRATE AM	The metric summarizes the whole landscape as the	> 0	1
	distribution	$= am(GYRATE[patch_{ii}])$	area weighted mean of the radius of gyration of all	= 0 if every patch is a single cell. Increases, without limit,	G
	(GYRATE)	where,	patches in the total landscape. GYRATE measures	when only one patch is present.	(]
	_	$\frac{Z}{Z}$ h	the distance from each cell to the patch centroid		
		$GYRATE = \sum_{i=1}^{n_{ijr}} \frac{n_{ijr}}{z}$	and is based on cell center-to-cell center distances.		
		r=1	The metrics characterizes both the patch area and		

compactness.

#### Frequency in reviewed papers

### 10

(Cheng et al., 2015; Das et al., 2020; Du et al., 2016; Gage & Cooper, 2017; A. Guo et al., 2020; B. Li et al., 2020; X. Wang et al., 2021; Weber et al., 2014; Yang et al., 2022; Zhao et al., 2020)

(Weber et al., 2014)

(Bera et al., 2022; Cheng et al., 2015; Connors et al., 2012; Li et al., 2017; Rakoto et al., 2021; X. Wang et al., 2021; Weber et al., 2014; Wu et al., 2021)

AREA MN (Cheng et al., 2015; Das et al., 2020; Ma & Peng, 2022; Rakoto et al., 2021) AREA\_SD (Du et al., 2016; Weber et al., 2014) AREA\_AM (Liu et al., 2018b) AREA CV (Weber et al., 2014) 1 GYRATE\_AM

(Liu et al., 2018b)

Metric category	Landscape metric	Calculation <sup>#</sup>	Description	Range	Fr
Shape metrics	Perimeter-area fractal dimension (PAFRAC)	$PAFRARC = \frac{2}{\beta}$ where $\beta$ is the slope of the regression of the area against the perimeter (logarithm) $N \sum_{i=1}^{m} \sum_{j=1}^{n} \ln a_{ij}$ $= a + N \sum_{i=1}^{m} \sum_{j=1}^{n} \ln p_{ij}$	It describes the patch complexity of the landscape while being scale independent. This means that increasing the patch size while not changing the patch form will not change the metric.	1≤PAFRAC≤2 Approaches 1 for shapes with very simple perimeters and approaches 2 for shapes with highly convoluted, plane- filling perimeters.	1 (1
	Shape index distribution (SHAPE_)	SHAPE_MN = mean(SHAPE[patch <sub>ij</sub> ]) SHAPE_AM = am(SHAPE[patch <sub>ij</sub> ]) SHAPE_SD = sd(SHAPE[patch <sub>ij</sub> ])	The total landscape is summarized as the mean / area weighted mean / standard deviation of each patch belonging to the total landscape.	<ul> <li>SHAPE_MN/AM = 0 if all patches are squares. Increases, without limit, as the shapes of patches become more complex.</li> <li>SHAPE_SD = 0 if all patches have an identical shape index. Increases, without limit, as the variation of the shape index increases.</li> </ul>	7 SH (( SH (1 SH
	Fractal index distribution (FRAC_)	FRAC_AM = am(FRAC[patch <sub>ij</sub> ]) FRAC_MN = mean(FRAC[patch <sub>ij</sub> ])	The metric summarizes the landscape as the mean / area weighted mean of the fractal dimension index of all patches belonging to class i.	1≤FRAC_MN≤2 Approaches 1 for a squared patch shape form and 2 for an irregular patch shape.	(. 9 (0 Li 20
Aggregation metrics	Contagion (CONTAG)	$CONTAG = 1 + \frac{\sum_{q=1}^{n_a} p_q \ln(p_q)}{2 \ln(t)}$	It is based on cell adjacencies and describes the probability of two random cells belonging to the same class. It is affected by both the dispersion and interspersion of classes. E.g., low class dispersion (= high proportion of like adjacencies) and low interspersion (= uneven distribution of pairwise adjacencies) lead to a high contagion value.	0 < Contag <=100 Approaches CONTAG = 0 if all cells are unevenly distributed and 100 indicates that all cells are equally adjacent to all other classes.	14 (J 20 20 H. 20
	Interspersion and juxtaposition index (IJI)	$IJI = \frac{-\sum_{i=1}^{m} \sum_{k=i+1}^{m} \left[ \left(\frac{e_{ik}}{E}\right) \ln \left(\frac{e_{ik}}{E}\right) \right]}{\ln(0.5[m(m-1)])}$ + 100	It describes the intermixing of classes (i.e. without considering like adjacencies - the diagonal of the adjacency table).	0 <iji≤100 Approaches 0 if a class is only adjacent to a single other class and equals 100 when a class is equally adjacent to all other classes.</iji≤100 	4 (I Ga
	Aggregation index (AI)	* 100 $AI = \left[\sum_{i=1}^{m} \left(\frac{g_{ii}}{max - g_{ii}}\right) P_i\right] (100)$	It equals the number of like adjacencies divided by the theoretical maximum possible number of like adjacencies for that class summed over each class for the entire landscape. The metric is based on he adjacency matrix and the single-count method	0 <= AI <= 100 Equals 0 for maximally disaggregated and 100 for maximally aggregated classes.	8 (0 20 Zh
	Splitting index (SPLIT)	$SPLIT = \frac{A^2}{\sum_{i=1}^m \sum_{j=1}^n a_{ij}^2}$	It describes the number of patches if all patches the landscape would be divided into equally sized patches.	1 <= SPLIT <= Number of cells squared Equals SPLIT = 1 if only one patch is present. Increases as the number of patches of class i increases and is limited if all cells are a patch	1 (.

#### Frequency in reviewed papers

(H. Liu & Q. H. Weng, 2009)

SHAPE AM

(Galletti et al., 2019; Ma & Peng, 2022; Weber et al., 2014) SHAPE MN

(Bera et al., 2022; Rakoto et al., 2021; Weber et al., 2014) SHAPE SD

(J. Chen, P. Du, et al., 2022; Du et al., 2016)

(Connors et al., 2012; Galletti et al., 2019; Li et al., 2017; H. Liu & Q. H. Weng, 2009; Liu et al., 2018b; X. Wang et al., 2021; Y. Wang et al., 2021; Weber et al., 2014; Yu et al., 2020)

#### 14

(J. Chen, P. Du, et al., 2022; Connors et al., 2012; Das et al., 2020; Du et al., 2016; Gage & Cooper, 2017; Galletti et al., 2019; Kamarianakis et al., 2017; Li et al., 2017; H. Liu & Q. H. Weng, 2009; Wu et al., 2021; Wu et al., 2014; Wu et al., 2019; Y. Zhang et al., 2022; Zhao et al., 2020)

(Das et al., 2020; Du et al., 2016; Gage & Cooper, 2017; Galletti et al., 2019)

(Gage & Cooper, 2017; A. Guo et al., 2020; Ma & Peng, 2022; X. Wang et al., 2021; Wu et al., 2021; Yang et al., 2022; Zhao et al., 2020)

(X. Wang et al., 2021)

Metric category	Landscape metric	Calculation <sup>#</sup>	Description	Range	F
	Landscape shape index (LSI)	$LSI = \frac{E}{\min E}$	It is the ratio between the actual landscape edge length and the hypothetical minimum edge length.	$LSI \ge 1$ = 1 when only one squared patch is present. Increases.	15
			The minimum edge length equals the edge length if	without limit, as the length of the actual edges increases.	D
			only one patch would be present.	i.e. the patches become less compact.	al
				1 1	W
					al
	Patch cohesion index	COHESION	It characterizes the connectedness of patches in the	0 < COHESION < 100	1
	(COHESION)	$\left( \sum_{i=1}^{m} \sum_{j=1}^{n} p_{ij} \right)$	total landscape. It can be used to assess if patches	Approaches COHESION = $0$ if patches become more	(
		$= 1 - \left( \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} p_{ij} \sqrt{a_{ij}}}{\sum_{i=1}^{m} \sum_{j=1}^{n} p_{ij} \sqrt{a_{ij}}} \right)$	are located aggregated or rather isolated and	isolated. Increases if patches become more aggregated.	
		$\begin{pmatrix} 1 \\ 1 \end{pmatrix}^{-1}$ 100	thereby COHESION gives information about the		
		$*\left(1-\frac{1}{\sqrt{Z}}\right)$ * 100	configuration of the landscape.		
	Number of patches	NP = N	It describes the fragmentation of the landscape,	Equals $NP = 1$ when only one patch is present and	4
	(NP)		however, does not necessarily contain information	increases, without limit, as the number of patches increases	(
			about the configuration or composition of the		Ya
			landscape.		
	Patch density (PD)	$PD = \frac{N}{M} * 10000 * 100$	It describes the fragmentation the landscape,	PD > 0	19
		A	however, does not necessarily contain information	Increases as the landscape gets patchier. Reaches its	(
			about the configuration or composition of the	maximum if every cell is a different patch.	D
			landscape. It is standardized to the area and		G
			comparisons among landscapes with different total		et
			area are possible.		ai.
	Landsoona division	DIVISION	It can be in as the probability that two randomly	$0 \leq -$ Division $\leq 1$	20
	index (DIVISION)		selected cells are not located in the same natch	0 < Division < 1 Equals DIVISION = 0 if only one patch is present	3
		$=\left(1-\sum_{i=1}^{m}\sum_{j=1}^{n}\left(\frac{a_{ij}}{2}\right)^{2}\right)$	screeted eens are not rocated in the same paten.	Approaches DIVISION = 1 if all patches of class i are	C
		$\begin{pmatrix} 1 & \sum_{i=1}^{n} \sum_{j=1}^{n} \begin{pmatrix} A \end{pmatrix} \end{pmatrix}$		single cells	
	Effective mesh size	$\sum_{i=1}^{m} \sum_{j=1}^{n} a_{j}^{2} = 1$	Because each patch is squared before the sum is	cell size / total area <= MESH <= total area	1
	(MESH)	$MESH = \frac{2l=12j=10lj}{A} * \frac{1}{10000}$	calculated and the sum is standardized by the total	Equals cell size/total area if class covers only one cell and	(
			landscape area, MESH is a relative measure of	equals total area if only one patch is present.	
			patch structure.		
	Euclidean nearest	ENN_MN	It summarizes the total landscape as the mean of	$ENN_MN > 0$	4
	neighbor distance	$= mean(ENN[patch_{ij}])$	each patch.	= 0 as the distance to the nearest neighbor decreases, i.e.	(
	distribution	where,		patches in the total landscape are more aggregated.	W
	(ENN_MN)	$ENN = h_{ij}$			
	Proximity index	n	It summarizes the total landscape as the mean of	PROX >0	1
	distribution (PROX)	$PROX = \sum \frac{a_{ijs}}{a_{ijs}}$	each patch belonging.	= 0 if all patches within the specified search radius. It	(
	(11011)	$\sum_{s=1}^{n} h_{ijs}$	1	increases as patches of the corresponding patch type	(·
				become less isolated and the patch type becomes less	
				fragmented in distribution.	

\* Confirmed by personal correspondence with the corresponding authors. # Calculation formulas and descriptions are adopted from McGarigal et al. (2012) and <a href="https://r-spatialecology.github.io/landscapemetrics/index.html">https://r-spatialecology.github.io/landscapemetrics/index.html</a> (accessed Oct. 2022). A area, p perimeter,  $n_{ii}^{core}$  core area of patch ij based on specified edge depths,  $g_{ii}$  number of like adjacencies between pixels of class type i based on the double-count method,  $e_{ik}$  total length of edge in landscape between patch types i and k,  $d_{ik}$  dissimilarity between patch types i

and k,  $c_{ijk}$  joining between patch j and k of the corresponding patch type based on a user specified threshold distance, min  $e_i$  minimum total length of edge of class i in terms of number of cell surfaces,  $h_{ijs}$  distance between patch ijs and patch ijs, based on patch

edge-to-edge distance computed from cell center to cell center.

#### Frequency in reviewed papers

#### 15

(Bera et al., 2022; Cheng et al., 2015; Connors et al., 2012; Das et al., 2020; Gage & Cooper, 2017; T. Li et al., 2020; Li et al., 2017; H. Liu & Q. H. Weng, 2009; Rakoto et al., 2021; X. Wang et al., 2021; Weber et al., 2014; Wu et al., 2021; Wu et al., 2019; Yang et al., 2022; Yu et al., 2020)

(H. Liu & Q. H. Weng, 2009; Sun et al., 2022)

#### 4

(Das et al., 2020; Gage & Cooper, 2017; Ma & Peng, 2022; Yang, He, Wang, et al., 2017)

#### 19

(Bera et al., 2022; Cheng et al., 2015; Connors et al., 2012; Das et al., 2020; Du et al., 2016; Gage & Cooper, 2017; Galletti et al., 2019; A. Guo et al., 2020; B. Li et al., 2020; Li et al., 2017; Ma & Peng, 2022; Rakoto et al., 2021; X. Wang et al., 2021; Y. Wang et al., 2021; Weber et al., 2014; Wu et al., 2021; Yu et al., 2020; Y. Zhang et al., 2022; Zhao et al., 2020) 3

(Gage & Cooper, 2017; Y. Wang et al., 2021; Wu et al., 2019)

(Yang et al., 2022)

### 4

(Cheng et al., 2015; Rakoto et al., 2021; Weber et al., 2014; Wu et al., 2021)

(H. Liu & Q. H. Weng, 2009)

Table B4 Studies that have included 3D metrics and their key findings

Citation	3D metrics		Key findings
	Quantify buildings	Quantify UGS	
(C. Yang et al., 2021)	Mean building height, building height index, mean building volume, building volume index, floor area ratio, building height variance	NA	2D metrics were found contributing more than 3D metrics to LST.
(Q. Wu et al., 2022)	Root mean square deviation of a surface, skewness of surface height distribution, mean height, maximum height, sky view factor	NA	Results of multiple regression and random forest models reveal that 3D m
(Chen et al., 2020)	NA	Mean tree height, maximum height of tree canopy, variance of tree canopy height, amplitude of tree canopy height, normalized tree canopy height variance	2D composition metrics and 3D metrics jointly may best explain LST van
(Yuan et al., 2021)	Building coverage ratio, mean building height, floor area ratio, sky view factor, low-rise buildings area ratio, mid-rise buildings area ratio, high-rise building area ratio	NA	Building metrics were found contributing more than UGS metrics. Building coverage ratio was found contributing the most, followed by high ratio.
(J. Chen et al., 2021)	Mean/maximum/variance height of buildings, normalized of building height, sky view factor achieved by buildings, building height value at 10th percentile, building height value at 90th percentile	Mean/maximum/variance of tree canopy height, normalized tree canopy height variance, 10th percentile tree height value, 90th percentile tree height value	During daytime, 2D metrics were found contributing more than 3D metric During daytime, 3D metrics of trees have better performance than those of
(Gage & Cooper, 2017)	Building height	Tree height	Contribution of 3D metrics varies among land cover clusters.
(Huang & Wang, 2019)	Shape coefficient, mean height, height variance, normalized height variance, sky view factor	NA	<ul><li>2D metrics were found contributing more than 3D metrics. Among 3D metrics most prominent.</li><li>Contribution of 3D landscape metrics of building varied among urban winter.</li></ul>
(WB. Wu et al., 2022)	Mean building height, volume of building	Mean tree height, volume of tree	3D metrics effectively improve the interpretation of SRHII. Landscape metrics' significance to SRHII varies across climate zones, see
(Yu et al., 2020)	Class level: volume, ED, PROX, CO, PD, ten-point average height, sur Landscape level: diversity, LSI, FRAC, PD, mean of height, root mea mean-square slope of a surface, skewness of surface height distribution interfacial area ratio, summit curvature of a surface, density of summit	nmit curvature of a surface, density of summit an square of height, ten-point average height, root- on, kurtosis of surface height distribution, developed nit	3D metrics may well explain LST without including 2D metrics. For vegetation coverage, 3D metrics can be treated as 2D metrics.
(Zeng et al., 2022)	Mean height, mean height standard deviation, high ratio, SHDI		Building metrics demonstrate greater influence. Varies by building and ve
(J. Chen, W. Zhan, et al., 2022)SEM model	SVFbuilding, mean height, variance of building height, maximum height of buildings	Variance of tree height, mean tree canopy height, maximum height of tree canopy	2D and 3D building structures showed much stronger indirect impacts on
(H. Zhang et al., 2022)	Mean building height, mean aspect ratio	Green volume	Interactions of 3D green volume and 2D LMs were significant. (PLSR in
(X. Chen et al., 2022)	mean height, mean volume, floor area ratio	NA	2D landscape metrics explained more of the variation in LST than 3D l while 3D landscape metrics had a stronger effect on LST in winter.
(J. Chen, P. Du, et al., 2022)	Maximum building height, mean building height, normalized variance of building height, 10/90 <sup>th</sup> percentile of building height	Maximum tree height, mean tree height, normalized variance of tree height, 10/90 <sup>th</sup> percentile of tree height	2D and 3D factors jointly demonstrated the best performaces. Multilevel
(Lyu et al., 2023)	Building height	Green volume, LAI	3D green volume demonstrates high relative importance.

netrics better explain LST variance than 2D metrics. riance both during daytime and nighttime.

ch-rise building area ratio and low-rise building area

ics. Opposite for nighttime. of buildings. Opposite for nighttime.

tetrics, mean height and sky view factor were found function zones and seasons, with the strongest in

asons and day and night.

egetation coverage. LST through horizontal and vertical tree structures

nteraction) landscape metrics in spring, summer, and autumn,

model for better performance than OLS model.

#### Appendix C Summary of meta-analysis results of Pearson correlation between patch,

#### class level landscape metrics and temperature indicators

Table C1 and C2 are summaries of meta-analysis results of Pearson correlation between patch and class level landscape metrics (LMs) and temperature indicators respectively. Detailed results of each combination of landscape metric and temperature indicator are shown in Appendix D.

The studies used for meta-analysis are identical to those demonstrated in Fig. 6 and Fig. 8. To ensure homogeneity among synthesized studies, all extracted Pearson correlations were calculated by using temperature indicators based on daytime LST. Their full information can be referred to in Appendix A.

I Ma	Temperature	Sub-group	Studies	Tatal samula sina	Dan dama effecte madel	II
LIVIS	indicators	(Climate Zone)	included	Total sample size	Kandom effects model	Heterogeneity
PARA	CE	С	3	342	[-0.83,0.88]	p<0.01
		D	1	300	N/A	N/A
		Overall	4	642	[-0.77,0.69]	p<0.01
	CI	А	1	4	N/A	N/A
		С	4	382	[-0.80,0.14]	p<0.01
		D	2	333	[-0.71,-0.59]	p=0.52
		Overall	7	719	[-0.76,-0.21]	p<0.01
	LST statistics	С	3	82	[0.17,0.63]	p=0.21
		D	1	300	N/A	N/A
		Overall	4	382	[0.30,0.47]	p=0.35
SHAPE	CE	А	4	532	[-0.01,0.28]	p=0.05
		В	1	15	N/A	N/A
		С	3	391	[-0.10,0.56]	p<0.01
		Overall	8	938	[-0.01,0.30]	p<0.01
	CI	А	3	270	[-0.13,0.11]	p=0.95
		В	1	15	N/A	N/A
		С	5	466	[0.05.0.49]	p<0.01
		Overall	9	751	[-0.07,0.30]	p<0.01
	LST statistics	С	3	668	[-0.45,-0.04]	p<0.01
		D	4	966	[-0.33,-0.21]	<mark>p=0.80</mark>
		Overall	7	1634	[-0.32,-0.18]	p=0.03

Table C1 Meta-analysis results of Pearson correlation between patch-level LMs and temperature indicators

Note: Results marked in yellow are constantly positive or negative pooled Pearson correlation with 95% confidence interval, and homogenous groups. Same below.

LMs	UGS type	Sub-group (Climata Zana)	Studies	Total sample size	Random effects model	Heterogeneity
ARFA MN	Vegetation		4	280	[-0 57 -0 29]	n=0.11
	vegetation	B	2	1025	[-0.72, 0.58]	p < 0.01
		с С	4	7869	[-0.30 -0.26]	p=0.01
		D	4	7608	[-0.02.0.90]	p<0.01
		Overall	14	16782	[-0.35.0.31]	p<0.01
	Tree	A	1	40	N/A	N/A
		С	1	25	N/A	N/A
		Overall	2	65	[-0.79,0.08]	p=0.03
	Grass	A	1	40	N/A	N/A
		С	1	25	N/A	N/A
		Overall	2	65	[-0.20,0.30]	p=0.36
LPI	Vegetation	В	3	1132	[-0.51,0.44]	p<0.01
		С	2	7629	<mark>[-0.47,-0.44]</mark>	<mark>p=0.39</mark>
		D	3	7599	<mark>[-0.61,-0.39]</mark>	p=0.01
		Overall	8	16360	[-0.56,-0.11]	p<0.01
	Tree	А	1	40	N/A	N/A
		В	1	66	N/A	N/A
		С	2	2275	[-0.73,-0.27]	p=0.10
		D	1	235	N/A	N/A
		Overall	5	2616	[-0.61,-0.19]	p<0.01
	Grass	А	1	40	N/A	N/A
		С	2	2275	[-0.26,-0.18]	<mark>p=0.35</mark>
		D	1	235	N/A	N/A
		Overall	4	2550	[-0.24,0.09]	p<0.01
ED	Vegetation	В	1	1000	N/A	N/A
		С	4	7835	[-0.49,-0.46]	p=0.76
		D	4	7608	[-0.54,0.67]	p<0.01
		Overall	9	16443	[-0.55,0.11]	p<0.01
	Tree	В	3	634	<mark>[-0.60,-0.49]</mark>	p=0.92
		С	2	2275	[-0.53,0.38]	p=0.02
		D	1	235	N/A	N/A
		Overall	6	3144	[-0.53,-0.13]	p<0.01
	Grass	В	1	500	N/A	N/A
		С	1	2250	N/A	N/A
		D	1	235	N/A	N/A
		Overall	3	2985	[-0.43,0.07]	p<0.01
SHAPE_MN	Vegetation	А	4	280	<mark>[-0.65,-0.33]</mark>	<mark>p=0.02</mark>

Table C2 Meta-analysis of Pearson correlation of class-level LMs and mean LST

I Ma	UCS true	Sub-group	Studies	T. A. Las and the star		<b>H</b>
LIVIS	UGS type	(Climate Zone)	included	iotai sampie size	Kandom effects model	Heterogeneity
		В	1	1000	N/A	N/A
		С	5	410	[-0.53,-0.30]	<mark>p=0.08</mark>
		D	3	327	[0.03,0.85]	p<0.01
		Overall	13	2017	[-0.48,0.09]	p<0.01
	Tree	А	1	40	N/A	N/A
		С	1	2250	N/A	N/A
		Overall	2	2290	[-0.34,-0.26]	<mark>p=0.50</mark>
	Grass	А	1	40	N/A	N/A
		С	1	2250	N/A	N/A
		Overall	2	2290	[-0.57,0.78]	p<0.01
LSI	Vegetation	В	1	107	N/A	N/A
		С	1	25	N/A	N/A
		D	5	645	[-0.06,0.52]	p<0.01
		Overall	7	777	[-0.25,0.39]	p<0.01
	Tree	В	1	500	N/A	N/A
		С	1	25	N/A	N/A
		D	1	58	N/A	N/A
		Overall	3	583	[-0.48,0.11]	p=0.02
	Grass	В	1	500	N/A	N/A
		D	1	58	N/A	N/A
		Overall	2	558	[-0.27,-0.11]	p=0.47
AI	Vegetation	А	4	280	[-0.77,-0.33]	p<0.01
		В	2	1025	[-0.45,0.08]	p=0.14
		С	5	410	[-0.61,-0.09]	p<0.01
		D	2	318	[-0.77,-0.10]	p<0.01
		Overall	13	2033	[-0.58,-0.30]	p<0.01
	Tree	А	1	40	N/A	N/A
		В	1	66	N/A	N/A
		D	1	235	N/A	N/A
		Overall	3	341	[-0.58,-0.03]	p<0.01
	Grass	А	1	40	N/A	N/A
		D	1	235	N/A	N/A
		Overall	2	275	[-0.19,0.21]	p=0.19
COHESION	Vegetation	С	1	60	N/A	N/A
		D	1	158	N/A	N/A
		Overall	2	218	<mark>[-0.69,-0.08]</mark>	p=0.01
	Tree	В	1	66	N/A	N/A
		С	1	25	N/A	N/A
		Overall	2	91	<mark>[-0.94,-0.40]</mark>	p<0.01

LMs	UGS type	Sub-group (Climate Zone)	Studies included	Total sample size	Random effects model	Heterogeneity
PD	Vegetation	А	1	100	N/A	N/A
		С	6	566	[-0.37,-0.11]	p=0.03
		D	5	645	[-0.54,0.24]	p<0.01
		Overall	12	1311	<b>[-0.40,-0.05]</b>	p<0.01
	Tree	В	1	500	N/A	N/A
		С	3	2300	[-0.77,0.35]	p<0.01
		D	2	293	[0.04,0.33]	p=0.25
		Overall	6	3093	[-0.46,0.23]	p<0.01
	Grass	В	1	500	N/A	N/A
		С	2	2275	[-0.31,0.41]	p=0.06
		D	2	293	[-0.53,0.28]	p<0.01
		Overall	5	3069	[-0.31,0.13]	p<0.01

**Appendix D** Meta-analysis of Pearson correlation patch, class level landscape metrics and temperature indicators

Study	Total	Correlation	COR	95%-CI	Weight (common)	Weight (random)
ClimateZone1 = B Pramanik & Punia, 2019	15 —		-0.51	[-0.81; 0.00]	1.7%	6.5%
ClimateZone1 = C						
Xiang Sun et al., 2020	52		-0.05	[-0.32; 0.22]	6.8%	11.5%
X. Tan et al., 2021	23		0.14	[-0.29; 0.52]	2.8%	8.5%
Cai et al., 2022	300	<del>     </del>	0.23	[0.12; 0.34]	41.0%	14.4%
X. Chen et al., 2021	23		0.50	[ 0.10; 0.75]	2.8%	8.5%
Du et al., 2017	68		- 0.54	[ 0.35; 0.69]	9.0%	12.2%
Common effect model	466		0.26	[ 0.18; 0.35]	62.3%	
Random effects model			0.28	[ 0.05; 0.49]		55.0%
Heterogeneity: $I^2 = 73\%$ , 1	$r^2 = 0.0543$	, p < 0.01				
ClimateZone1 = A	0.0		0.04		12 00/	12 00/
Li et al., 2022	90		-0.04	[-0.25; 0.17]	12.0%	12.9%
Li et al., 2022	73		0.00	[-0.23; 0.23]	9.7%	12.4%
L1 et al., 2022	107		0.00	[-0.19; 0.19]	14.4%	13.2%
Common effect model	270		-0.01	[-0.13; 0.11]	36.0%	
Random effects model $L^2$	0		-0.01	[-0.13; 0.11]		38.4%
Heterogeneity: $1^- = 0\%$ , $\tau^-$	= 0, p = 0.	.95				
Common effect model	751		0.15	[0.08.0.22]	100.0%	
Random effects model	/51		0.13	[-0.07; 0.30]	100.070	100.0%
Random encets moder			0.12	[ 0.07, 0.50]		100.070
		-0.5 0 0.5				
Heterogeneity: $I^2 = 77\%$	$t^2 = 0.0628$	p < 0.01				
Test for subgroup differences	s (fixed effe	et): $\gamma_2^2 = 19.50$ . df = 2 (n -	< 0.01)			
Test for subgroup differences	s (random ef	ffects): $\chi_2^2 = 9.11$ , df = 2 (	(p = 0.01)			

Fig. D1 Forest plot of Pearson correlation between patch-level SHAPE and cooling intensity

#### Fig. D2 Forest plot of Pearson correlation between patch-level SHAPE and cooling extent

Study	Total	Correlation	COR	95%-CI	Weight (common)	Weight (random)
ClimateZone = B Pramanik & Punia, 2019	15 -		-0.37	[-0.74; 0.18]	1.3%	5.6%
ClimateZone = A						
Li et al., 2022	90	·	-0.06	[-0.26; 0.15]	9.5%	13.8%
Li et al., 2022	73		0.10	[-0.13; 0.32]	7.7%	13.0%
Li et al., 2022	107		0.18	[-0.01; 0.36]	11.4%	14.3%
Shah et al., 2021	262		0.27	[ 0.15; 0.38]	28.3%	16.3%
Common effect model	532	$\diamond$	0.18	[ 0.09; 0.26]	56.9%	
Random effects model			0.14	[-0.01; 0.28]		57.4%
Heterogeneity: $I^2 = 62\%$ ,	$\tau^2 = 0.0133$	5 , p = 0.05				
ClimateZone = C						
Caj et al 2022	300		0.04	$[-0.07 \cdot 0.15]$	32.5%	16.5%
X Tan et al $2021$	23	i	0.14	[-0.29:0.52]	2.2%	7.8%
Du et al. $2017$	68		0.54	[ 0.34: 0.69]	7.1%	12.8%
Common effect model	391		0.14	[ 0.04: 0.24]	41.8%	
Random effects model			0.26	[-0.10; 0.56]		37.0%
Heterogeneity: $I^2 = 88\%$ ,	$\tau^2 = 0.0833$	3 , p < 0.01				
Common effect model	938		0.15	[009.022]	100.0%	
Random effects model	750		0.15	[-0.01; 0.30]		100.0%
2	2	-0.6 $-0.2$ 0 $0.2$ $0.4$ $0.6$				
Heterogeneity: $I^2 = 75\%$ ,	$\tau^2 = 0.038$	1, p < 0.01				
Test for subgroup differences	s (fixed eff	fect): $\chi_2^2 = 3.87$ , df = 2 (p = 0.14)				

Test for subgroup differences (fixed effect):  $\chi_2^2 = 3.87$ , df = 2 (p = 0.14) Test for subgroup differences (random effects):  $\chi_2^2 = 3.76$ , df = 2 (p = 0.15)

#### Fig. D3 Forest plot of Pearson correlation between patch-level SHAPE and LST statistics

Study	Total	Correlation	COR	95%-CI	Weight (common)	Weight (random)
Climate Zone = C Du et al., 2017 W. Zhou et al., 2022 Shih, 2017 Common effect model Random effects model Heterogeneity: $I^2 = 82\%$ , T	$ \begin{array}{c} 68 \\ 300 \\ 300 \\ 668 \end{array}^{2} = 0.0317 \\ . $		-0.46 -0.25 -0.08 -0.20 -0.25	[-0.63; -0.25] [-0.35; -0.14] [-0.19; 0.03] [-0.27; -0.12] [-0.45; -0.04]	4.0% 18.4% 18.4% 40.9%	7.6% 17.0% 17.0% 41.6%
Climate Zone = D W. Zhou et al., 2022 Chen et al., 2014b Yang, He, Yu, et al., 2017 W. Zhou et al., 2022 Common effect model Random effects model	300 300 66 300 966		-0.30 -0.29 -0.24 -0.23 -0.27	[-0.40; -0.19] [-0.39; -0.18] [-0.46; 0.00] [-0.34; -0.12] [-0.33; -0.21] [-0.33; -0.21]	18.4% 18.4% 3.9% 18.4% 59.1%	17.0% 17.0% 7.4% 17.0% 58.4%
Heterogeneity: $I = 0\%$ , $\tau$ Common effect model Random effects model Heterogeneity: $I^2 = 58\%$ , $\tau$	$1634$ $-0.6$ $^{2} = 0.0063$	-0.4 -0.2 0 0.2 p = 0.03	-0.24 -0.25 0.4 0.6	[-0.29; -0.20] [-0.32; -0.18]	100.0%	100.0%

Test for subgroup differences (fixed effect):  $\chi_1^2 = 2.44$ , df = 1 (p = 0.12) Test for subgroup differences (random effects):  $\chi_1^2 = 0.04$ , df = 1 (p = 0.85)



Fig. D4 Forest plot of Pearson correlation between patch-level PARA and cooling intensity

Heterogeneity:  $I^2$  = 89% ,  $\tau^2$  = 0.2153 , p < 0.01 $\begin{array}{l} \chi^2_2 = 26.60,\, df = 2 \quad (p < 0.01 \ ) \\ \chi^2_2 = 0.93,\, df = 2 \quad (p = 0.63 \ ) \end{array}$ Test for subgroup differences (fixed effect):

Test for subgroup differences (random effects):



#### Fig. D5 Forest plot of Pearson correlation between patch-level PARA and cooling extent

Heterogeneity:  $I^2 = 96\%$ ,  $\tau^2 = 0.8816$ , p < 0.01Test for subgroup differences (fixed effect):  $\chi_1^2$  $\chi_1^2 = 25.18, df = 1 \quad (p < 0.01)$  $\chi_1^2 = 0.83, df = 1 \quad (p = 0.36)$ Test for subgroup differences (random effects):

Fig. D6 Forest plot of Pearson correlation between patch-level PARA and LST statistics

Study	Total	Correlation	COR	95%-CI	Weight (common)	Weight (random)
Climate Zone = C		1				
Wang et al., 2018	18		0.20	[-0.30; 0.61]	4.1%	4.1%
Shih, 2016	40		0.36	[ 0.06; 0.61]	10.0%	10.0%
Wang et al., 2022	24		- 0.64	[ 0.32; 0.83]	5.7%	5.7%
Common effect model	82		0.42	[ 0.22; 0.59]	19.7%	
Random effects model			0.43	[ 0.17; 0.63]		19.7%
Heterogeneity: $I^2 = 36\%$	$\tau_{0}^{2} = 0.0214$ ,	p = 0.21				
Climate Zone = D						
Chen et al., 2014b	300		0.38	[ 0.28; 0.47]	80.3%	80.3%
Common effect model	382		0.39	[ 0.30: 0.47]	100.0%	
Random effects model			0.39	[ 0.30; 0.47]		100.0%
		-0.5 0 0.5				
Heterogeneity: $I^2 = 8\%$	, $\tau^2 < 0.0001$ , $p$	= 0.35				

Test for subgroup differences (fixed effect):  $\chi_1^2 = 0.16$ , df = 1 (p = 0.69) Test for subgroup differences (random effects):  $\chi_1^2 = 0.12$ , df = 1 (p = 0.73)

Fig. D7 Forest plot of Pearson correlation between class-level AREA\_MN of urban vegetation coverage and mean LST

Study	Total	Correlation	COR	95%–CI	Weight (common)	Weight (random)
ClimateZone = A Estoque et al., 2017 Estoque et al., 2017 Estoque et al., 2017 Simwanda et al., 2019 Common effect model Random effects model Heterogeneity: $I^2 = 51\%$	$ \begin{array}{c} 60\\ 60\\ 100\\ 280\\ , \tau^2 = 0.0159, 1 \end{array} $	p = 0.11	-0.59 -0.52 -0.32 -0.32 -0.43 -0.44	$\begin{bmatrix} -0.73; -0.39 \\ [-0.68; -0.31] \\ [-0.53; -0.07] \\ [-0.48; -0.13] \\ [-0.52; -0.32] \\ \hline [-0.57; -0.29] \end{bmatrix}$	0.3% 0.3% 0.3% 0.6% 1.6%	7.0% 7.0% 7.0% 7.2%  28.3%
ClimateZone = B Lu et al., 2020 Athukorala & Murayama, 20 Common effect model Random effects model Heterogeneity: $I^2 = 93\%$	$1000 \\ 21  25 \\ 1025 \\ \tau^2 = 0.2981 , 1$	p < 0.01	0.25 -0.50 0.23 -0.12	[0.19; 0.30] [-0.75; -0.13] [0.17; 0.29] [-0.72; 0.58]	<b>6.0%</b> <b>0.1%</b> 6.1%	7.3% 6.6%  14.0%
ClimateZone = C Ma & Peng, 2022 Simwanda et al., 2019 Simwanda et al., 2019 Simwanda et al., 2019 L. Yang et al., 2021 He et al., 2021 Tang et al., 2023 Common effect model Random effects model Heterogeneity: $I^2 = 0\%$ ,	$100 \\ 100 \\ 100 \\ 7569 \\ 7869 \\ \tau^{2} = 0, p = 0.91$		$\begin{array}{r} -0.39 \\ -0.31 \\ -0.28 \\ -0.22 \\ -0.42 \\ -0.28 \\ -0.31 \\ -0.28 \\ \hline -0.28 \end{array}$	$\begin{bmatrix} -0.48; -0.12 \\ [-0.45; -0.09] \\ [-0.40; -0.03] \\ [-0.30; -0.26] \\ [-0.30; -0.26] \\ [-0.30; -0.26] \end{bmatrix}$	0.0% 0.6% 0.6% 0.0% 45.2% 0.0% 46.9%	0.0% 7.2% 7.2% 7.2% 0.0% 7.3% 0.0% 
ClimateZone = D Li et al., 2013 Li et al., 2013 Li et al., 2013 He et al., 2021 Common effect model Random effects model Heterogeneity: $I^2 = 99\%$	$109 \\ 109 \\ 109 \\ 7281 \\ 7608 \\ , \tau^{2} = 0.5863 , 1$	+ • • • • • • • • • • • • • • • • • • •	$\begin{array}{r} 0.52 \\ + 0.84 \\ + 0.89 \\ -0.27 \\ -0.22 \\ \hline 0.62 \end{array}$	$\begin{bmatrix} 0.37; \ 0.65 \end{bmatrix} \\ \begin{bmatrix} 0.77; \ 0.89 \end{bmatrix} \\ \begin{bmatrix} 0.84; \ 0.92 \end{bmatrix} \\ \begin{bmatrix} -0.29; \ -0.25 \end{bmatrix} \\ \begin{bmatrix} -0.24; \ -0.20 \end{bmatrix} \\ \begin{bmatrix} -0.02; \ 0.90 \end{bmatrix}$	0.6% 0.6% 0.6% 43.5% 45.4%	7.2% 7.2% 7.2% 7.3% 
Common effect model Random effects model Heterogeneity: $I^2 = 99\%$	16782 , $\tau^2 = 0.4194$ , 1	-0.5 0 0.5 p < 0.01	-0.23 -0.02	[-0.24; -0.21] [-0.35; 0.31]	100.0%	100.0%

Test for subgroup differences (fixed effect):  $\chi_3^2 = 262.04$ , df = 3 (p < 0.01) Test for subgroup differences (random effects):  $\chi_3^2 = 11.24$ , df = 3 (p = 0.01)

Fig. D8 Forest plot of Pearson correlation between class-level AREA\_MN of tree canopy coverage and mean LST



Fig. D9 Forest plot of Pearson correlation between class-level AREA MN of grassland coverage and mean LST



Test for subgroup differences (random effects):

Study	Total	Correlation	COR	95%-CI	Weight (common)	Weight (random)
ClimateZone = A Masoudi & Tan, 2019 Masoudi et al., 2019 Masoudi et al., 2019 Masoudi et al., 2019			-0.45 -0.72 -0.45 -0.36		0.0% 0.0% 0.0% 0.0%	0.0% 0.0% 0.0% 0.0%
ClimateZone = B Lu et al., 2020 Li et al., 2018 Athukorala & Murayama, 2021 Common effect model Random effects model Heterogeneity: $I^2 = 92\%$ , $\tau^2$	1000 107 25 1132 = 0.1963 , p < 0.0	* *	0.32 0.04 -0.54 0.28 -0.05	[0.27; 0.38] [-0.15; 0.23] [-0.77; -0.19] [0.23; 0.33] [-0.51; 0.44]	6.1% 0.6% 0.1% 6.9%	13.3% 12.5% 10.0% 
ClimateZone = C B. Li et al., 2020 Ma & Peng, 2022 Guo et al., 2019 Guo et al., 2019 Guo et al., 2019 Guo et al., 2019 Masoudi et al., 2019 He et al., 2021 Common effect model Random effects model Heterogeneity: $I^2 = 0\%$ , $\tau^2 =$	60 7569 + 7629 ♦ ♦		$\begin{array}{r} -0.54 \\ -0.60 \\ -0.79 \\ -0.64 \\ -0.63 \\ -0.43 \\ -0.59 \\ -0.46 \\ \hline -0.46 \end{array}$	[-0.70; -0.33] [-0.47; -0.44] [-0.47; -0.44] [-0.47; -0.44]	0.3% 0.0% 0.0% 0.0% 0.0% 0.0% 46.3% 46.7%	11.9% 0.0% 0.0% 0.0% 0.0% 0.0% 13.4%  25.2%
ClimateZone = D Amani-Beni et al., 2019 Ren et al., 2014 He et al., 2021 Common effect model Random effects model Heterogeneity: $I^2 = 77\%$ , $\tau^2$	160 158 7281 7599 ♦ = 0.0139 , p = 0.0		-0.45 -0.63 -0.46 -0.47 -0.51	[-0.57; -0.32] [-0.72; -0.53] [-0.48; -0.45] [-0.48; -0.45] [-0.61; -0.39]	1.0% 0.9% 44.6% 46.5%	12.8% 12.8% 13.4% 
Random effects model	-0.6	-0.2 0 0.2 0.6	-0.42	[-0.43; -0.41] [-0.56; -0.11]	100.0%	100.0%

Fig. D10 Forest plot of Pearson correlation between class-level LPI of urban vegetation coverage and mean LST

 $\begin{array}{ll} \mbox{Heterogeneity:} & l^2=99\% \ , \ \tau^2=0.1349 \ , \ p\ < 0.01 \\ \mbox{Test for subgroup differences (fixed effect):} & \chi_2^2=649.44, \ df=2 \ (p\ < 0.01 \ ) \\ \mbox{Test for subgroup differences (random effects):} & \chi_2^2=3.74, \ df=2 \ (p\ = 0.15 \ ) \end{array}$ 

StudyTotalCorrelationCOR $95\%$ -CI (common) (randorClimateZone = A Athukorala & Murayama, 202040 $-0.25$ [ $-0.52$ ; 0.07] $1.4\%$ $17.7$ ClimateZone = B $-0.25$ [ $-0.52$ ; 0.07] $1.4\%$ $17.7$	n) 7% )% )%
ClimateZone = A         Athukorala & Murayama, 2020       40 $-0.25$ $[-0.52; 0.07]$ $1.4\%$ $17.7$ ClimateZone = B $-0.25$ $[-0.52; 0.07]$ $1.4\%$ $17.7$	7% )% )%
ClimateZone = A $-0.25$ [-0.52; 0.07] $1.4\%$ $17.7$ ClimateZone = B $-0.25$ [-0.52; 0.07] $1.4\%$ $17.7$	7% )% )%
ClimateZone = B	)% )%
ClimateZone = B	)% )%
	)% )%
Rhee et al 2014 $66 \rightarrow -0.60 [-0.74; -0.42] 2.4\% 200$	)%
	)%
ClimateZone = C	)%
J. Chen et al., 2021	70/
Zhou et al., 2017 -0.80 0.0% 0.0	J/0
Zhou et al., 2017 . –0.59 0.0% 0.0	)%
Zhou et al., 2011 2250 -0.45 [-0.48; -0.42] 86.4% 24.4	1%
Zhou & Cao, 20200.27 0.0% 0.0	)%
Wang et al., 2023 . "t -0.45 0.0% 0.0	)%
Wang et al., 20230.24 0.0% 0.0	)%
Wang et al., 2023 . 0.0% 0.0	)%
Karunaratne et al., 2022 25 $$	3%
Common effect model 2275 $\bullet$ -0.45 [-0.48; -0.42] 87.2%	
Random effects model $-0.54 \ [-0.73; -0.27] \ -39.2$	2%
Heterogeneity: $I^2 = 64\%$ , $\tau^2 = 0.0403$ , p = 0.10	
ClimateZone = D	10/
Y ao et al., $2020$ 235 $-0.10$ $-0.22$ ; $0.03$ $8.9\%$ $23.1$ X Ware et al. 2021 $0.57$ $0.0\%$ $0.0\%$ $0.4\%$	1%0
X. wang et al., $2021$ . $-0.57$ $0.0\%$ $0.0$	J%
Common effect model $2616$ $\Rightarrow$ $-0.43$ $[-0.46; -0.39]$ $100.0%$	
Random effects model $-0.42 = -0.61 = -0.101$ $ 100 ($	)%
	,/0
-0.5 0 0.5	

Fig. D11 Forest plot of Pearson correlation between class-level LPI of tree canopy coverage and mean LST

Heterogeneity:  $I^2 = 90\%$ ,  $\tau^2 = 0.0694$ , p < 0.01Test for subgroup differences (fixed effect):  $\chi_3^2 = 36.83$ , df = 3 (p < 0.01) Test for subgroup differences (random effects):  $\chi_3^2 = 21.93$ , df = 3 (p < 0.01)



Fig. D12 Forest plot of Pearson correlation between class-level LPI of grassland coverage and mean LST

Test for subgroup differences (fixed effect):  $\chi_2^2 = 14.24$ , df = 2 (p < 0.01) Test for subgroup differences (random effects):  $\chi_2^2 = 14.24$ , df = 2 (p < 0.01)

34

						Weight	Weight
Study	Total	Corre	lation	COR	95%-CI	(common)	(random)
		i :	1				
ClimateZone = A Masoudi & Tan. 2010				0.27		0.0%	0.0%
Masoudi et al. 2019	•		. ·	0.27		0.0%	0.0%
Masoudi et al., 2019	•			0.07		0.0%	0.0%
Masoudi et al., 2019	•		. 	0.07		0.0%	0.0%
Widsouul et al., 2019	•			0.27		0.070	0.070
ClimateZone = B							
Lu et al 2020	1000	-		-0.42	$[-0.47 \cdot -0.37]$	6.1%	11.5%
Rahimi et al 2021	1000	6		-0.27	[ 0.17, 0.57]	0.0%	0.0%
Tummi et ul., 2021	•			0.27		0.070	0.070
ClimateZone = C							
Li et al., 2011	25 —			-0.57	[-0.79; -0.23]	0.1%	10.0%
B. Li et al., 2020	60 -			-0.56	[-0.71; -0.36]	0.3%	10.9%
Kowe et al., 2021				-0.37		0.0%	0.0%
Guo et al., 2019				0.54		0.0%	0.0%
Guo et al., 2019				0.69		0.0%	0.0%
Guo et al., 2019				0.71		0.0%	0.0%
Guo et al., 2019				0.91		0.0%	0.0%
Yu et al., 2020		1		-0.20		0.0%	0.0%
Masoudi et al., 2019			1	0.36		0.0%	0.0%
Naeem et al., 2018		1		-0.20		0.0%	0.0%
L. Yang et al., 2021			1	0.43		0.0%	0.0%
He et al., 2021	7569	+		-0.47	[-0.49; -0.46]	46.1%	11.5%
G. Zhou et al., 2019	181	<u>+</u> +		-0.47	[-0.58; -0.35]	1.1%	11.3%
Terfa et al., 2020	. '			-0.67		0.0%	0.0%
Common effect model	7835	•		-0.47	[-0.49; -0.46]	47.7%	
Random effects model		۵		-0.47	[-0.49; -0.46]		43.6%
Heterogeneity: $I^2 = 0\%$ ,	$\tau^2 = 0, p = 0.76$						
Climate Zana – D							
$\frac{\text{ClimateZone} - D}{\text{Li et al. 2013}}$	100			0.02	[_0.16: 0.21]	0.6%	11 10/
Lietal., $2013$	109			0.02	[-0.10, 0.21]	0.0%	11.170
Li et al., $2013$	109			$\rightarrow$ 0.15	$\begin{bmatrix} 0.04, 0.33 \end{bmatrix}$	0.0%	11.170
Nacemental $2013$	109			-0.37	[0.07, 0.85]	0.0%	0.0%
He et al. $2010$	7281	+		-0.63	$[-0.64 \cdot -0.62]$	14 3%	11 5%
Common effect model	7608	0		-0.60	$\begin{bmatrix} 0.04, 0.02 \end{bmatrix}$	44.370	11.370
Random effects model	7008	V		0.00	$\begin{bmatrix} 0.02, 0.59 \end{bmatrix}$	40.370	11 9%
Heterogeneity: $I^2 = 00\%$	$\tau^2 = 0.5045$ p	< 0.01		0.10	[ 0.34, 0.07]		44.970
1101010genency. 1 - 9970	, i = 0.3043 , p	<ul><li>∨.01</li></ul>					
Common effect model	16443	0		-0.53	[-0.540.52]	100.0%	
Random effects model	10775			-0.25	[-0.55, 0.11]		100.0%
			+	0.23	[ 0.55, 0.11]		100.070
		-0.5	0 05				
Heterogeneity: $I^2 = 99\%$	$\tau^2 = 0.3041$ n	< 0.01	- 0.0				
	, , P	~ • • •					

Fig. D13 Forest plot of Pearson correlation between class-level ED of urban vegetation coverage and mean LST

Test for subgroup differences (fixed effect):  $\chi_2^2 = 147.10$ , df = 2 (p < 0.01) Test for subgroup differences (random effects):  $\chi_2^2 = 6.38$ , df = 2 (p = 0.04)

						Weight	Weight
Study	Total	Correla	ation	COR	95%-CI	(common)	(random)
ClimateZone - R		2					
Rhee et al $2014$	66 —			-0.53	$[-0.68 \cdot -0.33]$	2 0%	15.9%
Rhee et al. 2014	68 —			-0.52	[-0.67, -0.32]	2.0%	16.0%
Yan et al 2019	500 -	- i		-0.52	[-0.61; -0.49]	15.9%	18.8%
Shi & Zhao 2022	200	2		-0.12	[ 0.01, 0.15]	0.0%	0.0%
Common effect model	634	$\diamond$		-0.55	[-0.60: -0.49]	20.0%	
Random effects model	<	$\diamond$		-0.55	[-0.60; -0.49]		50.6%
Heterogeneity: $I^2 = 0\%$ ,	$\tau^2 = 0, p = 0.9$	92					
	· *	) ) )					
ClimateZone = C		1					
Chen et al., 2020		2	I	0.33		0.0%	0.0%
J. Chen et al., 2021			I	0.28		0.0%	0.0%
Wu et al., 2014	25	· · · · ·	+	0.20	[-0.21; 0.55]	0.7%	11.9%
Zhao et al., 2020		3 I 3		-0.30		0.0%	0.0%
Zhou et al., 2017	•	1 )		-0.58		0.0%	0.0%
Zhou et al., 2017		1 1		-0.56		0.0%	0.0%
Zhou et al., 2011	2250			-0.30	[-0.34; -0.26]	71.9%	19.2%
Common effect model	2275	$\diamond$		-0.30	[-0.33; -0.26]	72.6%	
Random effects model	2	)		-0.09	[-0.53; 0.38]		31.1%
Heterogeneity: $1^2 = 83\%$	$\tau^{2} = 0.1104$	p = 0.02					
ClimateZone - D		1					
Dugord et al $2014$		4 4		-0.26		0.0%	0.0%
Vac et al. $2020$	235	i		-0.11	$[-0.24 \cdot 0.02]$	7 4%	18.3%
X Wang et al 2021	255			-0.16	[ 0.24, 0.02]	0.0%	0.0%
A. Wang et al., 2021		) ) 1		0.10		0.070	0.070
Common effect model	3144	$\diamond$		-0.34	[-0.37: -0.31]	100.0%	
Random effects model	-			-0.34	[-0.53; -0.13]		100.0%
	Г						
	-0	.6 -0.4 -0.2 0	0.2 0.4 0	0.6			
Heterogeneity: $I^2 = 93\%$	$\tau^2 = 0.0728$	p < 0.01		0.01.)			

Fig. D14 Forest plot of Pearson correlation between class-level ED of tree canopy coverage and mean LST

Test for subgroup differences (fixed effect):  $\chi_2^2 = 61.78$ , df = 2 (p < 0.01) Test for subgroup differences (random effects):  $\chi_2^2 = 44.92$ , df = 2 (p < 0.01)

					Weight	Weight
Study	Total	Correlation	COR	95%-CI	(common)	(random)
ClimateZone = B						
Yan et al., 2019	500	- 8	-0.41	[-0.48; -0.34]	16.7%	33.5%
Shi & Zhao, 2022			-0.07		0.0%	0.0%
ClimateZone = C						
Zhao et al., 2020			-0.31		0.0%	0.0%
Zhou et al., 2011	2250		-0.18	[-0.22; -0.14]	75.5%	34.4%
ClimateZone = D						
Dugord et al., 2014			0.09		0.0%	0.0%
Yao et al., 2020	235	· · · · · ·	0.04	[-0.08; 0.17]	7.8%	32.1%
X. Wang et al., 2021		1 0	-0.27		0.0%	0.0%
Common effect model	2985	$\diamond$	-0.20	[-0.24; -0.17]	100.0%	
Random effects model	_		-0.19	[-0.43; 0.07]		100.0%
	I		I			
	-0.4	-0.2 0 0.2	0.4			
Heterogeneity: $I^2 = 95\%$	$, \tau^2 = 0.0539$ , p	< 0.01				

Fig. D15 Forest plot of Pearson correlation between class-level ED of grassland coverage and mean LST

Test for subgroup differences (fixed effect):  $\chi_2^2 = 42.27$ , df = 2 (p < 0.01) Test for subgroup differences (random effects):  $\chi_2^2 = 42.27$ , df = 2 (p < 0.01)

Fig. D16 Forest plot of Pearson correlation between class-level SHAPE\_MN of urban vegetation coverage and mean LST

						Weight	Weight
Study	Total	Correlation		COR	95%-CI	(common)	(random)
ClimateZone = A	60	1					
Estoque et al., 2017	60 -	*		-0.72	[-0.82; -0.57]	2.9%	7.6%
Estoque et al., 2017	60			-0.47	[-0.65; -0.25]	2.9%	7.6%
Estoque et al., 2017	60			-0.38	[-0.58; -0.15]	2.9%	7.6%
Simwanda et al., 2019	100			-0.42	[-0.57; -0.24]	4.9%	7.7%
Common effect model	280			-0.50	[-0.59; -0.41]	13.5%	
Random effects model	2			-0.51	[-0.65; -0.33]		30.5%
Heterogeneity: $I^2 = 69\%$	$, \tau^2 = 0.0350$	, p = 0.02					
ClimateZone = B							
Lu et al., 2020	1000			-0.22	[-0.27; -0.16]	50.4%	8.0%
ClimateZone = C	60				5 0 4 5 0 0 4 3	<b>a</b>	<b>-</b> (0)
B. Li et al., 2020	60			-0.22	[-0.45; 0.04]	2.9%	7.6%
Wu & Zhang, 2018	50 ·			-0.63	[-0.77; -0.42]	2.4%	7.5%
Simwanda et al., 2019	100			-0.49	[-0.63; -0.32]	4.9%	7.7%
Simwanda et al., 2019	100			-0.42	[-0.57; -0.24]	4.9%	7.7%
Simwanda et al., 2019	100			-0.34	[-0.50; -0.15]	4.9%	7.7%
L. Yang et al., 2021			I	0.25		0.0%	0.0%
Tang et al., 2023				-0.30		0.0%	0.0%
X. Tan et al., 2021		1 1		-0.64		0.0%	0.0%
Common effect model	410	$\diamond$		-0.42	[-0.50; -0.33]	20.0%	
Random effects model	2			-0.42	[-0.53; -0.30]		38.3%
Heterogeneity: $I^2 = 53\%$	$, \tau^2 = 0.0142$	, p = 0.08					
ClimateZone = D							
Li et al 2013	109			0.16	$[-0.03 \cdot 0.34]$	5 4%	7.8%
Li et al. $2013$	109			0.48	$\begin{bmatrix} 0.02, 0.01 \end{bmatrix}$	5.4%	7.8%
Li et al. 2013	109			+ 0.84	$\begin{bmatrix} 0.02, 0.01 \end{bmatrix}$	5 4%	7.8%
Common effect model	327		$\diamond$	0.56	[0.48, 0.63]	16.1%	
Random effects model	0 = 1			> 0.56	$\begin{bmatrix} 0.03 \\ 0.85 \end{bmatrix}$		23.3%
Heterogeneity: $I^2 = 97\%$	$, \tau^2 = 0.2808$	, p < 0.01		0.20	[0.00, 0.00]		20.070
	0015			0.1-	F 0 01 0 100	100.001	
Common effect model	2017	$\diamond$		-0.17	[-0.21; -0.13]	100.0%	
Random effects model				-0.21	[-0.48; 0.09]		100.0%
		-0.5 0	0.5				

Heterogeneity:  $I^2 = 97\%$ ,  $\tau^2 = 0.3104$ , p < 0.01Test for subgroup differences (fixed effect):  $\chi_3^2 = 277.54$ , df = 3 (p < 0.01) Test for subgroup differences (random effects):  $\chi_3^2 = 23.76$ , df = 3 (p < 0.01)



Fig. D17 Forest plot of Pearson correlation between class-level SHAPE\_MN of tree canopy coverage and mean LST

Fig. D18 Forest plot of Pearson correlation between class-level SHAPE\_MN of grassland coverage and mean LST

Study	Total		Correlation	1	COR	95%-CI	Weight (common)	Weight (random)
ClimateZone = A Athukorala & Murayama, 20	20 40				0.56	[ 0.30; 0.74]	1.6%	48.2%
ClimateZone = C				• • •				
Zhao et al., 2020		1		•	-0.43		0.0%	0.0%
Zhou et al., 2011	2250		-+-		-0.22	[-0.26; -0.18]	98.4%	51.8%
Wang et al., 2023			10	•	-0.16		0.0%	0.0%
Wang et al., 2023		I.		•	-0.48		0.0%	0.0%
Wang et al., 2023					-0.21		0.0%	0.0%
Common effect model	2290		<b>\</b>	• • •	-0.21	[-0.25; -0.17]	100.0%	
Random effects model					• 0.19	[-0.57; 0.78]		100.0%
		-0.6	-0.2 0 0	.2 0.4 0.6				

Heterogeneity:  $I^2=96\%$  ,  $\tau^2=0.3568\,$  , p<0.01

Test for subgroup differences (fixed effect):  $\chi_1^2 = 26.98$ , df = 1 (p < 0.01) Test for subgroup differences (random effects):  $\chi_1^2 = 26.98$ , df = 1 (p < 0.01)

Weight Weight Total Correlation COR 95%-CI (common) Study (random) ClimateZone = AMasoudi & Tan, 2019 0.30 0.0% 0.0% Masoudi et al., 2019 0.0% 0.0% 0.16 Masoudi et al., 2019 0.19 0.0% 0.0% Masoudi et al., 2019 0.30 0.0% 0.0% ClimateZone = B Li et al., 2018 107 -0.25 [-0.42; -0.06] 13.8% 14.5% Rahimi et al., 2021 -0.340.0% 0.0% ClimateZone = C Li et al., 2011 25 -0.54 [-0.77; -0.19] 2.9% 12.3% Ma & Peng, 2022 0.47 0.0% 0.0% Masoudi et al., 2019 0.38 0.0% 0.0% Naeem et al., 2018 0.39 0.0% 0.0% Tang et al., 2023 -0.040.0% 0.0% ClimateZone = D Li et al., 2013 109 -0.09 [-0.27; 0.10] 14.0% 14.5% Li et al., 2013 [-0.18; 0.20] 109 14.0% 14.5% 0.01 Li et al., 2013 109 0.48 [0.32; 0.61] 14.0% 14.5% Amani-Beni et al., 2019 0.08 160 [-0.07; 0.23]20.8% 14.8% Ren et al., 2014 158 0.64 [0.54; 0.72] 20.5% 14.8% Naeem et al., 2018 0.08 0.0% 0.0% Common effect model 645 0.27 [0.20; 0.34] 83.3%  $\bigcirc$ Random effects model 0.25 [-0.06; 0.52] 73.2% Heterogeneity:  $I^2=94\%$  ,  $\tau^2=0.1261$  , p<0.01777 Common effect model 0.18 [0.11; 0.25] 100.0% Random effects model 0.08 [-0.25; 0.39]100.0% -0.2 0 0.2 0.4 0.6 -0.6 Heterogeneity:  $I^2 = 95\%$ ,  $\tau^2 = 0.1873$ , p < 0.01

Fig. D19 Forest plot of Pearson correlation between class-level LSI of urban vegetation coverage and mean LST

 $\begin{array}{ll} \mbox{Heterogeneity:} & I^2=95\% \ , \ \tau^2=0.1873 \ , \ p<0.01 \\ \mbox{Test for subgroup differences (fixed effect):} & \chi_2^2=39.98, \ df=2 \ (p<0.01 \ ) \\ \mbox{Test for subgroup differences (random effects):} & \chi_2^2=11.82, \ df=2 \ (p<0.01 \ ) \end{array}$ 



Fig. D20 Forest plot of Pearson correlation between class-level LSI of tree canopy coverage and mean LST

Test for subgroup differences (random effects):

Study	Total	Correlation	COR	95%-CI	Weight (common)	Weight (random)
ClimateZone = A Masoudi & Tan, 2019			-0.28		0.0%	0.0%
ClimateZone = B Yan et al., 2019 Shi & Zhao, 2022	500		-0.19 -0.03	[-0.27; -0.10]	90.0% 0.0%	90.0% 0.0%
ClimateZone = C Zhao et al., 2020			-0.26		0.0%	0.0%
ClimateZone = D Yin et al., 2019 X. Wang et al., 2021	58 -		-0.28 -0.44	[-0.50; -0.03]	10.0% 0.0%	10.0% 0.0%
Common effect model Random effects model	558		-0.20 -0.20	[-0.27; -0.11] [-0.27; -0.11]	100.0%	100.0%
2		-0.4 -0.2 0 0.2	0.4			

Fig. D21 Forest plot of Pearson correlation between class-level LSI of grassland coverage and mean LST

Heterogeneity:  $I^2 = 0\%$ ,  $\tau^2 = 0$ , p = 0.47 $\begin{aligned} \chi_1^2 = 0.52, \, df = 1 \quad (p = 0.47 \,) \\ \chi_1^2 = 0.52, \, df = 1 \quad (p = 0.47 \,) \end{aligned}$ Test for subgroup differences (fixed effect): Test for subgroup differences (random effects):

Weight Weight COR Study Total Correlation 95%-CI (common) (random) ClimateZone = AMasoudi & Tan, 2019 -0.350.0% 0.0% Estoque et al., 2017 60 -0.71[-0.82; -0.56] 2.9% 7.4% 2.9% 7.4% Estoque et al., 2017 60 -0.71[-0.82; -0.55] 2.9% 7.4% Estoque et al., 2017 60 -0.67[-0.79; -0.50] Masoudi et al., 2019 -0.470.0% 0.0% -0.35Masoudi et al., 2019 0.0% 0.0% Masoudi et al., 2019 -0.280.0% 0.0% Simwanda et al., 2019 100 -0.19[-0.37; 0.01] 4.9% 8.0% Common effect model 280 -0.55 [-0.63; -0.46] 13.4%  $\frown$ Random effects model -0.60 [-0.77; -0.33] 30.3% Heterogeneity:  $I^2 = 89\%$ ,  $\tau^2 = 0.1043$ , p < 0.01 ClimateZone = B Lu et al., 2020 1000 + -0.11 [-0.17; -0.05] 50.0% 8.7% Athukorala & Murayama, 2021 25 -0.40 [-0.69; -0.01] 1.1% 6.0%  $\diamond$ Common effect model -0.12 [-0.18; -0.06] 51.1% Random effects model -0.20 [-0.45; 0.08] 14.7%Heterogeneity:  $I^2 = 54\%$ ,  $\tau^2 = 0.0269$ , p = 0.14ClimateZone = C60 2.9% 7.4% B. Li et al., 2020 0.05 [-0.21; 0.30]Ma & Peng, 2022 -0.390.0% 0.0% Wu & Zhang, 2018 50 -0.53 [-0.70; -0.29]2.4% 7.2% Masoudi et al., 2019 -0.460.0% 0.0% 100 -0.704.9% 8.0% Simwanda et al., 2019 [-0.79; -0.58] [-0.49; -0.13]Simwanda et al., 2019 100 -0.324.9% 8.0% Simwanda et al., 2019 100 [-0.42; -0.05]-0.244.9% 8.0% L. Yang et al., 2021 -0.100.0% 0.0% X. Tan et al., 2021 -0.620.0% 0.0% Common effect model 410 19.8% -0.40[-0.48; -0.31] Random effects model -0.38 [-0.61; -0.09] 38.5% Heterogeneity:  $I^2 = 89\%$ ,  $\tau^2 = 0.1065$ , p < 0.01 ClimateZone = D Amani-Beni et al., 2019 160 -0.31 [-0.45; -0.17] 7.9% 8.3% Ren et al., 2014 158 -0.66 [-0.74; -0.56] 7.8% 8.2% Common effect model 318 -0.51 [-0.58; -0.42] 15.6% Random effects model -0.51 [-0.77; -0.10] 16.5% Heterogeneity:  $I^2 = 94\%$ ,  $\tau^2 = 0.1030$ , p < 0.01 -0.30 [-0.34; -0.26] Common effect model 2033 100.0%  $\diamond$ 100.0% Random effects model -0.45 [-0.58; -0.30] -0.50 0.5

Fig. D22 Forest plot of Pearson correlation between class-level AI of urban vegetation coverage and mean LST

 $\begin{array}{ll} \mbox{Heterogeneity:} & I^2=93\% \ , \ \tau^2=0.0968 \ , \ p<0.01 \\ \mbox{Test for subgroup differences (fixed effect):} & \chi_3^2=86.27, \ df=3 \ (p<0.01 \ ) \\ \mbox{Test for subgroup differences (random effects):} & \chi_3^2=5.11, \ df=3 \ (p=0.16 \ ) \end{array}$ 

Study	Total	Correla	tion	COR	95%-CI	Weight (common)	Weight (random)
ClimateZone = A Athukorala & Murayama, 2020	) 40		-	-0.27	[-0.54; 0.04]	11.1%	28.7%
ClimateZone = B Rhee et al., 2014	66 —	-		-0.57	[-0.71; -0.38]	19.0%	32.8%
ClimateZone = C Zhao et al., 2020 Zhou & Cao, 2020 Wang et al., 2020 Wang et al., 2020 Wang et al., 2020		· · ·	1	-0.30 -0.18 -0.28 -0.11 0.22		$\begin{array}{c} 0.0\% \\ 0.0\% \\ 0.0\% \\ 0.0\% \\ 0.0\% \end{array}$	$\begin{array}{c} 0.0\% \\ 0.0\% \\ 0.0\% \\ 0.0\% \\ 0.0\% \end{array}$
ClimateZone = D Yao et al., 2020 X. Wang et al., 2021	235	-		-0.13 -0.56	[-0.26; -0.01]	69.9% 0.0%	38.6% 0.0%
Common effect model Random effects model	341 Г			-0.24 -0.33	[-0.34; -0.14] [-0.58; -0.03]	100.0%	100.0%
Heterogeneity: $I^2 = 85\%$ , Test for subgroup differences	-0. $r^2 = 0.0614$ , s (fixed effect)	6 - 0.4 - 0.2  0 p < 0.01 ): $\chi_2^2 = 13.07$	0.2 0.4 0.6 $f = 2$ (p < 0.4	01)			

Fig. D23 Forest plot of Pearson correlation between class-level AI of tree canopy coverage and mean LST

 $\chi_2^2 = 13.07, df = 2 (p < 0.01)$ Test for subgroup differences (random effects):

Fig. D24 Forest plot of Pearson correlation between class-level AI of grassland coverage and mean LST

Study	Total	Correlation	COR	95%-CI	Weight (common)	Weight (random)
ClimateZone = A Athukorala & Murayama, 2	020 40		0.18	[-0.14; 0.46]	13.8%	28.6%
ClimateZone = C						
Zhao et al., 2020		1	-0.10		0.0%	0.0%
Wang et al., 2020			-0.13		0.0%	0.0%
Wang et al., 2020			-0.72		0.0%	0.0%
Wang et al., 2020			-0.47		0.0%	0.0%
ClimateZone = D						
Yao et al., 2020	235		-0.05	[-0.18; 0.08]	86.2%	71.4%
X. Wang et al., 2021			0.14		0.0%	0.0%
Common effect model	275		-0.02	[-0.14; 0.10]	100.0%	
Random effects model	<b>—</b>		0.01	[-0.19; 0.21]		100.0%
	-0.4	-0.2 0 0.2	0.4			

Heterogeneity:  $I^2 = 41\%$ ,  $\tau^2 = 0.0108$ , p = 0.19Test for subgroup differences (fixed effect):  $\chi_1^2 = 1.69$ , df = 1 (p = 0.19) Test for subgroup differences (random effects):  $\chi_1^2 = 1.69$ , df = 1 (p = 0.19)



Fig. D25 Forest plot of Pearson correlation between class-level COHESION of urban vegetation coverage and mean LST

#### Fig. D26 Forest plot of Pearson correlation between class-level COHESION of tree canopy coverage and mean LST



Test for subgroup differences (random effects):

						Weight	Weight	
Study	Total Correlation			COR	95%-CI	(common)	(random)	
5						. ,	× /	
ClimateZone = A								
Masoudi & Tan 2019				0.28		0.0%	0.0%	
Masoudi et al. 2019	•			0.20		0.0%	0.0%	
Masoudi et al. 2019	•			0.24		0.0%	0.0%	
Masoudi et al., 2019	•			0.28		0.0%	0.0%	
Masoudi et al., 2019				0.28	F 0 <b>F0</b> 0 101	0.0%	0.0%	
Simwanda et al., 2019	100			-0.36	[-0.52; -0.18]	7.6%	8.4%	
ClimateZone = B								
Rahimi et al., 2021				-0.34		0.0%	0.0%	
ClimateZone = C								
Li et al., 2011	25 —			-0.60	[-0.81; -0.27]	1.7%	6.4%	
B. Li et al., 2020	60			-0.10	[-0.35: 0.16]	4.5%	7.9%	
Ma & Peng 2022				-0.00	[	0.0%	0.0%	
Masoudi et al 2019	•		1	0.34		0.0%	0.0%	
Simwanda et al. 2019	100			-0.19	[-0.37:0.01]	7.6%	8 /1%	
Simwanda et al. 2010	100			0.15	$\begin{bmatrix} 0.37, 0.01 \end{bmatrix}$	7.070	0. <del>4</del> /0	
Simwanda et al., 2019	100			-0.13	[-0.34, 0.03]	7.070	0.470	
Simwanda et al., 2019	100			-0.13	[-0.32; 0.06]	/.6%	8.4%	
Naeem et al., 2018	•		I	0.43		0.0%	0.0%	
L. Yang et al., 2021				-0.29		0.0%	0.0%	
G. Zhou et al., 2019	181			-0.39	[-0.51; -0.26]	14.0%	8.8%	
Tang et al., 2023				-0.06		0.0%	0.0%	
Terfa et al., 2020			I.	0.71		0.0%	0.0%	
Common effect model	566			-0.25	[-0.33; -0.17]	43.0%		
Random effects model		$\Leftrightarrow$		-0.24	[-0.37: -0.11]		48.5%	
Heterogeneity: $I^2 = 61\%$	$\tau^2 = 0.0154$	n = 0.03			[,]			
fictorogeneity. 1 0170,	0.0154	, p 0.05						
ClimatoZona – D								
$\frac{1}{1} \frac{1}{1} \frac{1}{2} \frac{1}$	100			0.60	[ 0.71, 0.46]	0.20/	0 50/	
Li et al., 2013	109			-0.60	[-0.71; -0.46]	8.3%	8.3%	
Li et al., 2013	109			-0.45	[-0.59; -0.29]	8.3%	8.5%	
L1 et al., 2013	109			-0.33	[-0.49; -0.15]	8.3%	8.5%	
Amani-Beni et al., 2019	160			0.09	[-0.07; 0.24]	12.3%	8.8%	
Ren et al., 2014	158			0.47	[ 0.34; 0.58]	12.2%	8.7%	
Naeem et al., 2018				0.26		0.0%	0.0%	
Common effect model	645	$\diamond$		-0.11	[-0.18; -0.03]	49.4%		
Random effects model				-0.18	[-0.54; 0.24]		43.0%	
Heterogeneity: $I^2 = 97\%$	$\tau^2 = 0.2255$	p < 0.01						
		, p						
Common effect model	1311			-0.19	$[-0.24 \cdot -0.14]$	100.0%		
Random effects model	1.511			-0.23	$\begin{bmatrix} 0.27, 0.14 \end{bmatrix}$	100.070	100.0%	
Random encets model				0.23	[ 0.0, 0.03]		100.070	
		0.5 0	0.5					
··· · · · · · · · · · · · · · · · · ·	2 0 1 1 1	-0.5 0	0.5					
Heterogeneity: $I^2 = 92\%$ ,	$\tau^{-} = 0.1011$	, p < 0.01						
Test for subgroup differences (fixed effect): $\gamma_2^2 = 10.09$ , df = 2 (p < 0.01)								

Fig. D27 Forest plot of Pearson correlation between class-level PD of urban vegetation coverage and mean LST

Heterogeneity:  $I^2 = 92\%$ ,  $\tau^2 = 0.1011$ , p < 0.01Test for subgroup differences (fixed effect):  $\chi_2^2 = 10.09$ , df = 2 (p < 0.01) Test for subgroup differences (random effects):  $\chi_2^2 = 1.35$ , df = 2 (p = 0.51)

						Weight	Weight	
Study	Total	Correl	ation	COR	95%-CI	(common)	(random)	
ClimateZone = B								
Yan et al., 2019	500			-0.34	[-0.41; -0.26]	16.2%	18.0%	
Shi & Zhao, 2022		1		-0.10		0.0%	0.0%	
ClimateZone = C				0.00		0.00/	0.00/	
Chen et al., 2020				0.36		0.0%	0.0%	
J. Chen et al., 2021				0.41	F 0 00 0 001	0.0%	0.0%	
Wu et al., 2014	25 —	• •		-0.63	[-0.82; -0.32]	0.7%	14.8%	
Zhao et al., 2020		t :		-0.14		0.0%	0.0%	
Zhou et al., 2011	2250			0.31	[ 0.27; 0.35]	73.1%	18.1%	
Zhou & Cao, 2020		10 :		-0.15		0.0%	0.0%	
Karunaratne et al., 2022	2 25 -	<b>-</b>		-0.56	[-0.78; -0.21]	0.7%	14.8%	
Common effect model	2300		¦ ♦	0.29	[0.25; 0.33]	74.5%		
Random effects model	_			-0.31	[-0.77; 0.35]		47.6%	
Heterogeneity: $I^2 = 95\%$	$, \tau^2 = 0.3406$	, p < 0.01						
ClimateZone = D								
Dugord et al., 2014		1		-0.31		0.0%	0.0%	
Yin et al., 2019	58			0.30	[0.05: 0.52]	1.8%	16.6%	
Yao et al., 2020	235			0.14	[0.01: 0.26]	7.5%	17.8%	
X Wang et al 2021				0.48	[ •••••, ••=•]	0.0%	0.0%	
Common effect model	293		$\checkmark$	0.17	[0.06:0.28]	9.3%		
Random effects model	2,0			0.18	$\begin{bmatrix} 0.00, 0.20 \end{bmatrix}$		34 4%	
Heterogeneity: $I^2 = 26\%$	$\tau^2 = 0.0039$	p = 0.25		0.10	[ 0.01, 0.00]		0 1.170	
11eterogeneroj. 1 2070	, • • • • • • • • • • • • • • • • • • •	, p 0.20						
Common effect model	3093		•	0.18	[0.15; 0.22]	100.0%		
Random effects model				-0.13	[-0.46; 0.23]		100.0%	
					. , -1			
		-0.5 (	0.5					
Heterogeneity: $I^2 = 98\%$ , $\tau^2 = 0.1968$ , $p < 0.01$								
That for subgroup differences (fixed effect): $x^2 = 174.18$ df = 2 ( $n < 0.01$ )								

Fig. D28 Forest plot of Pearson correlation between class-level PD of tree canopy coverage and mean LST

 $\begin{array}{ll} \mbox{Heterogeneity:} & I^2 = 98\%, \ \tau^2 = 0.1968 \ , \ p < 0.01 \\ \mbox{Test for subgroup differences (fixed effect):} & \chi_2^2 = 174.18, \ df = 2 \quad (p < 0.01 \ ) \\ \mbox{Test for subgroup differences (random effects):} & \chi_2^2 = 36.51, \ df = 2 \quad (p < 0.01 \ ) \\ \end{array}$ 

Study	Total	Correlation	COR	95%-CI	Weight (common)	Weight (random)
Study	Total	conclution	COR	<i>JJ</i> /0 CI	(common)	(randoni)
ClimateZone = B						
Yan et al., 2019	500		-0.26	[-0.34: -0.17]	16.3%	23.0%
Shi & Zhao, 2022		1	-0.05	L ,]	0.0%	0.0%
,						
ClimateZone = C						
Zhao et al., 2020		1	-0.19		0.0%	0.0%
Zhou et al., 2011	2250		0.20	[0.16; 0.24]	73.6%	23.6%
Karunaratne et al., 2	022 25 -	+ !	-0.19	[-0.55; 0.22]	0.7%	13.2%
Common effect mode	el 2275	$\diamond$	0.20	[0.16; 0.24]	74.3%	
Random effects mod	el		0.06	[-0.31; 0.41]		36.8%
Heterogeneity: $I^2 = 7$	$1\%$ , $\tau^2 = 0.0567$	, p = 0.06				
ClimateZone = D						
Dugord et al., 2014			0.10		0.0%	0.0%
Yin et al., 2019	58 -		-0.38	[-0.58; -0.13]	1.8%	18.0%
Yao et al., 2020	235		0.05	[-0.07; 0.18]	7.6%	22.1%
X. Wang et al., 2021	l.	1	-0.16		0.0%	0.0%
Common effect mode	el 293		-0.03	[-0.15; 0.08]	9.4%	
Random effects mod	el		-0.15	[-0.53; 0.28]		40.2%
Heterogeneity: $I^2 = 8$	$9\%$ , $\tau^2 = 0.0905$	, p < 0.01				
Common effect mode	el 3068		0.10	[0.07; 0.14]	100.0%	
Random effects mod	el		-0.10	[-0.31; 0.13]		100.0%
				. / 1		
		-0.4 -0.2 0 0.2	0.4			
Heterogeneity: $I^2 = 9$	$6\%$ , $\tau^2 = 0.0567$	, p < 0.01				

Fig. D29 Forest plot of Pearson correlation between class-level PD of grassland coverage and mean LST

 $\begin{array}{ll} \mbox{Heterogeneity:} & 1^2 = 96\%, \ \tau^2 = 0.0567 \ , \ p < 0.01 \\ \mbox{Test for subgroup differences (fixed effect):} & \chi_2^2 = 92.61, \ df = 2 \ (p < 0.01) \\ \mbox{Test for subgroup differences (random effects):} & \chi_2^2 = 2.84, \ df = 2 \ (p = 0.24) \\ \end{array}$ 

#### References

- Amani-Beni, M., Zhang, B., Xie, G.-D., & Shi, Y. (2019). Impacts of Urban Green Landscape Patterns on Land Surface Temperature: Evidence from the Adjacent Area of Olympic Forest Park of Beijing, China. Sustainability, 11(2). https://doi.org/10.3390/su11020513
- An, H., Cai, H., Xu, X., Qiao, Z., & Han, D. (2022). Impacts of Urban Green Space on Land Surface Temperature from Urban Block Perspectives. *Remote Sensing*, 14(18). https://doi.org/10.3390/rs14184580
- Asgarian, A., Amiri, B. J., & Sakieh, Y. (2014). Assessing the effect of green cover spatial patterns on urban land surface temperature using landscape metrics approach. Urban Ecosystems, 18(1), 209-222. https://doi.org/10.1007/s11252-014-0387-7
- Athukorala, D., & Murayama, Y. (2020). Spatial Variation of Land Use/Cover Composition and Impact on Surface Urban Heat Island in a Tropical Sub-Saharan City of Accra, Ghana. Sustainability, 12(19). https://doi.org/10.3390/su12197953
- Athukorala, D., & Murayama, Y. (2021). Urban Heat Island Formation in Greater Cairo: Spatio-Temporal Analysis of Daytime and Nighttime Land Surface Temperatures along the Urban–Rural Gradient. *Remote Sensing*, 13(7). https://doi.org/10.3390/rs13071396
- Bao, T., Li, X., Zhang, J., Zhang, Y., & Tian, S. (2016). Assessing the Distribution of Urban Green Spaces and its Anisotropic Cooling Distance on Urban Heat Island Pattern in Baotou, China. *ISPRS International Journal* of *Geo-Information*, 5(2). https://doi.org/10.3390/ijgi5020012
- Bartesaghi-Koc, C., Osmond, P., & Peters, A. (2020). Quantifying the seasonal cooling capacity of 'green infrastructure types' (GITs): An approach to assess and mitigate surface urban heat island in Sydney, Australia. *Landscape and Urban Planning*, 203. https://doi.org/10.1016/j.landurbplan.2020.103893
- Bera, D., Das Chatterjee, N., Mumtaz, F., Dinda, S., Ghosh, S., Zhao, N., Bera, S., & Tariq, A. (2022). Integrated Influencing Mechanism of Potential Drivers on Seasonal Variability of LST in Kolkata Municipal Corporation, India. *Land*, 11(9). https://doi.org/10.3390/land11091461
- Cai, Y.-B., Wu, Z.-J., Chen, Y.-H., Wu, L., & Pan, W.-B. (2022). Investigate the Difference of Cooling Effect between Water Bodies and Green Spaces: The Study of Fuzhou, China. *Water*, 14(9). https://doi.org/10.3390/w14091471
- Cao, X., Onishi, A., Chen, J., & Imura, H. (2010). Quantifying the cool island intensity of urban parks using ASTER and IKONOS data. *Landscape and Urban Planning*, 96(4), 224-231. https://doi.org/10.1016/j.landurbplan.2010.03.008
- Chakraborti, S., Banerjee, A., Sannigrahi, S., Pramanik, S., Maiti, A., & Jha, S. (2019). Assessing the dynamic relationship among land use pattern and land surface temperature: A spatial regression approach. *Asian Geographer*, 36(2), 93-116. https://doi.org/10.1080/10225706.2019.1623054
- Chen, A., Yao, L., Sun, R., & Chen, L. (2014a). How many metrics are required to identify the effects of the landscape pattern on land surface temperature? *Ecological Indicators*, 45, 424-433. https://doi.org/10.1016/j.ecolind.2014.05.002
- Chen, A., Yao, X. A., Sun, R., & Chen, L. (2014b). Effect of urban green patterns on surface urban cool islands and its seasonal variations. *Urban Forestry & Urban Greening*, *13*(4), 646-654. https://doi.org/10.1016/j.ufug.2014.07.006
- Chen, D., Zhang, F., Zhang, M., Meng, Q., Jim, C. Y., Shi, J., Tan, M. L., & Ma, X. (2022). Landscape and vegetation

traits of urban green space can predict local surface temperature. *Sci Total Environ*, 825, 154006. https://doi.org/10.1016/j.scitotenv.2022.154006

- Chen, J., Du, P., Jin, S., Ding, H., Chen, C., Xu, Y., Feng, L., Guo, G., Zheng, H., & Huang, M. (2022). Unravelling the multilevel and multi-dimensional impacts of building and tree on surface urban heat islands. *Energy and Buildings*, 259. https://doi.org/10.1016/j.enbuild.2022.111843
- Chen, J., Jin, S., & Du, P. (2020). Roles of horizontal and vertical tree canopy structure in mitigating daytime and nighttime urban heat island effects. *International Journal of Applied Earth Observation and Geoinformation*, 89. https://doi.org/10.1016/j.jag.2020.102060
- Chen, J., Zhan, W., Du, P., Li, L., Li, J., Liu, Z., Huang, F., Lai, J., & Xia, J. (2022). Seasonally disparate responses of surface thermal environment to 2D/3D urban morphology. *Building and Environment*, 214. https://doi.org/10.1016/j.buildenv.2022.108928
- Chen, J., Zhan, W., Jin, S., Han, W., Du, P., Xia, J., Lai, J., Li, J., Liu, Z., Li, L., Huang, F., & Ding, H. (2021). Separate and combined impacts of building and tree on urban thermal environment from two- and three-dimensional perspectives. *Building and Environment*, 194. https://doi.org/10.1016/j.buildenv.2021.107650
- Chen, X., Wang, Z., & Bao, Y. (2021). Cool island effects of urban remnant natural mountains for cooling communities: A case study of Guiyang, China. Sustainable Cities and Society, 71. https://doi.org/10.1016/j.scs.2021.102983
- Chen, X., Wang, Z., Bao, Y., Luo, Q., & Wei, W. (2022). Combined impacts of buildings and urban remnant mountains on thermal environment in multi-mountainous city. *Sustainable Cities and Society*, 87. https://doi.org/10.1016/j.scs.2022.104247
- Cheng, X., Wei, B., Chen, G., Li, J., & Song, C. (2015). Influence of Park Size and Its Surrounding Urban Landscape Patterns on the Park Cooling Effect. *Journal of Urban Planning and Development*, 141(3). https://doi.org/10.1061/(asce)up.1943-5444.0000256
- Connors, J. P., Galletti, C. S., & Chow, W. T. L. (2012). Landscape configuration and urban heat island effects: assessing the relationship between landscape characteristics and land surface temperature in Phoenix, Arizona. *Landscape Ecology*, 28(2), 271-283. https://doi.org/10.1007/s10980-012-9833-1
- Das, D. N., Chakraborti, S., Saha, G., Banerjee, A., & Singh, D. (2020). Analysing the dynamic relationship of land surface temperature and landuse pattern: A city level analysis of two climatic regions in India. *City and Environment Interactions*, 8. https://doi.org/10.1016/j.cacint.2020.100046
- Du, C., Jia, W., Chen, M., Yan, L., & Wang, K. (2022). How can urban parks be planned to maximize cooling effect in hot extremes? Linking maximum and accumulative perspectives. J Environ Manage, 317, 115346. https://doi.org/10.1016/j.jenvman.2022.115346
- Du, H., Cai, W., Xu, Y., Wang, Z., Wang, Y., & Cai, Y. (2017). Quantifying the cool island effects of urban green spaces using remote sensing Data. Urban Forestry & Urban Greening, 27, 24-31. https://doi.org/10.1016/j.ufug.2017.06.008
- Du, H., Zhou, F., Cai, W., Cai, Y., & Xu, Y. (2021). Thermal and Humidity Effect of Urban Green Spaces with Different Shapes: A Case Study of Shanghai, China. Int J Environ Res Public Health, 18(11). https://doi.org/10.3390/ijerph18115941
- Du, S., Xiong, Z., Wang, Y.-C., & Guo, L. (2016). Quantifying the multilevel effects of landscape composition and configuration on land surface temperature. *Remote Sensing of Environment*, 178, 84-92. https://doi.org/10.1016/j.rse.2016.02.063

- Dugord, P.-A., Lauf, S., Schuster, C., & Kleinschmit, B. (2014). Land use patterns, temperature distribution, and potential heat stress risk – The case study Berlin, Germany. *Computers, Environment and Urban Systems*, 48, 86-98. https://doi.org/10.1016/j.compenvurbsys.2014.07.005
- Ekwe, M. C., Adamu, F., Gana, J., Nwafor, G. C., Usman, R., Nom, J., Onu, O. D., Adedeji, O. I., Halilu, S. A., & Aderoju, O. M. (2020). The effect of green spaces on the urban thermal environment during a hot-dry season: a case study of Port Harcourt, Nigeria. *Environment, Development and Sustainability*, 23(7), 10056-10079. https://doi.org/10.1007/s10668-020-01046-9
- Estoque, R. C., Murayama, Y., & Myint, S. W. (2017). Effects of landscape composition and pattern on land surface temperature: An urban heat island study in the megacities of Southeast Asia. *Sci Total Environ*, 577, 349-359. https://doi.org/10.1016/j.scitotenv.2016.10.195
- Fan, H., Yu, Z., Yang, G., Liu, T. Y., Liu, T. Y., Hung, C. H., & Vejre, H. (2019). How to cool hot-humid (Asian) cities with urban trees? An optimal landscape size perspective. *Agricultural and Forest Meteorology*, 265, 338-348. https://doi.org/10.1016/j.agrformet.2018.11.027
- Feng, L., Zhao, M., Zhou, Y., Zhu, L., & Tian, H. (2020). The seasonal and annual impacts of landscape patterns on the urban thermal comfort using Landsat. *Ecological Indicators*, 110. https://doi.org/10.1016/j.ecolind.2019.105798
- Feng, X., & Myint, S. W. (2016). Exploring the effect of neighboring land cover pattern on land surface temperature of central building objects. *Building and Environment*, 95, 346-354. https://doi.org/10.1016/j.buildenv.2015.09.019
- Feyisa, G. L., Dons, K., & Meilby, H. (2014). Efficiency of parks in mitigating urban heat island effect: An example from Addis Ababa. Landscape and Urban Planning, 123, 87-95. https://doi.org/10.1016/j.landurbplan.2013.12.008
- Gage, E. A., & Cooper, D. J. (2017). Relationships between landscape pattern metrics, vertical structure and surface urban Heat Island formation in a Colorado suburb. Urban Ecosystems, 20(6), 1229-1238. https://doi.org/10.1007/s11252-017-0675-0
- Galletti, C. S., Li, X., & Connors, J. P. (2019). Establishing the relationship between urban land-cover configuration and night time land-surface temperature using spatial regression. *International Journal of Remote Sensing*, 40(17), 6752-6774. https://doi.org/10.1080/01431161.2019.1594432
- Gao, Z., Zaitchik, B. F., Hou, Y., & Chen, W. (2022). Toward park design optimization to mitigate the urban heat Island: Assessment of the cooling effect in five U.S. cities. *Sustainable Cities and Society*, 81. https://doi.org/10.1016/j.scs.2022.103870
- Greene, C. S., & Kedron, P. J. (2018). Beyond fractional coverage: A multilevel approach to analyzing the impact of urban tree canopy structure on surface urban heat islands. *Applied Geography*, 95, 45-53. https://doi.org/10.1016/j.apgeog.2018.04.004
- Guo, A., Yang, J., Sun, W., Xiao, X., Xia Cecilia, J., Jin, C., & Li, X. (2020). Impact of urban morphology and landscape characteristics on spatiotemporal heterogeneity of land surface temperature. *Sustainable Cities and Society*, 63. https://doi.org/10.1016/j.scs.2020.102443
- Guo, G., Wu, Z., Cao, Z., Chen, Y., & Yang, Z. (2020). A multilevel statistical technique to identify the dominant landscape metrics of greenspace for determining land surface temperature. *Sustainable Cities and Society*, 61. https://doi.org/10.1016/j.scs.2020.102263
- Guo, G., Wu, Z., Cao, Z., Chen, Y., & Zheng, Z. (2021). Location of greenspace matters: a new approach to

investigating the effect of the greenspace spatial pattern on urban heat environment. *Landscape Ecology*, 36(5), 1533-1548. https://doi.org/10.1007/s10980-021-01230-w

- Guo, G., Wu, Z., & Chen, Y. (2019). Complex mechanisms linking land surface temperature to greenspace spatial patterns: Evidence from four southeastern Chinese cities. *Sci Total Environ*, 674, 77-87. https://doi.org/10.1016/j.scitotenv.2019.03.402
- He, C., Zhou, L., Yao, Y., Ma, W., & Kinney, P. L. (2021). Cooling effect of urban trees and its spatiotemporal characteristics: A comparative study. *Building and Environment*, 204. https://doi.org/10.1016/j.buildenv.2021.108103
- Hou, H., & Estoque, R. C. (2020). Detecting Cooling Effect of Landscape from Composition and Configuration: An Urban Heat Island Study on Hangzhou. Urban Forestry & Urban Greening, 53. https://doi.org/10.1016/j.ufug.2020.126719
- Hu, Y., Dai, Z., & Guldmann, J. M. (2021). Greenspace configuration impact on the urban heat island in the Olympic Area of Beijing. *Environ Sci Pollut Res Int*. https://doi.org/10.1007/s11356-020-12086-z
- Huang, M., Cui, P., & He, X. (2018). Study of the Cooling Effects of Urban Green Space in Harbin in Terms of Reducing the Heat Island Effect. *Sustainability*, 10(4). https://doi.org/10.3390/su10041101
- Huang, R., Yang, M., Lin, G., Ma, X., Wang, X., Huang, Q., & Zhang, T. (2022). Cooling Effect of Green Space and Water on Urban Heat Island and the Perception of Residents: A Case Study of Xi'an City. *Int J Environ Res Public Health*, 19(22). https://doi.org/10.3390/ijerph192214880
- Huang, X., & Wang, Y. (2019). Investigating the effects of 3D urban morphology on the surface urban heat island effect in urban functional zones by using high-resolution remote sensing data: A case study of Wuhan, Central China. *ISPRS Journal of Photogrammetry and Remote Sensing*, 152, 119-131. https://doi.org/10.1016/j.isprsjprs.2019.04.010
- Jaganmohan, M., Knapp, S., Buchmann, C. M., & Schwarz, N. (2016). The Bigger, the Better? The Influence of Urban Green Space Design on Cooling Effects for Residential Areas. J Environ Qual, 45(1), 134-145. https://doi.org/10.2134/jeq2015.01.0062
- Kamarianakis, Y., Li, X., Turner, B. L., & Brazel, A. J. (2017). On the effects of landscape configuration on summer diurnal temperatures in urban residential areas: application in Phoenix, AZ. *Frontiers of Earth Science*, 13(3), 445-463. https://doi.org/10.1007/s11707-017-0678-4
- Karunaratne, S., Athukorala, D., Murayama, Y., & Morimoto, T. (2022). Assessing Surface Urban Heat Island Related to Land Use/Land Cover Composition and Pattern in the Temperate Mountain Valley City of Kathmandu, Nepal. *Remote Sensing*, 14(16). https://doi.org/10.3390/rs14164047
- Ke, X., Men, H., Zhou, T., Li, Z., & Zhu, F. (2021). Variance of the impact of urban green space on the urban heat island effect among different urban functional zones: A case study in Wuhan. Urban Forestry & Urban Greening, 62. https://doi.org/10.1016/j.ufug.2021.127159
- Kim, J. H., Gu, D., Sohn, W., Kil, S. H., Kim, H., & Lee, D. K. (2016). Neighborhood Landscape Spatial Patterns and Land Surface Temperature: An Empirical Study on Single-Family Residential Areas in Austin, Texas. Int J Environ Res Public Health, 13(9). https://doi.org/10.3390/ijerph13090880
- Kong, F., Yin, H., James, P., Hutyra, L. R., & He, H. S. (2014). Effects of spatial pattern of greenspace on urban cooling in a large metropolitan area of eastern China. *Landscape and Urban Planning*, 128, 35-47. https://doi.org/10.1016/j.landurbplan.2014.04.018
- Kong, F., Yin, H., Wang, C., Cavan, G., & James, P. (2014). A satellite image-based analysis of factors contributing to

the green-space cool island intensity on a city scale. Urban Forestry & Urban Greening, 13(4), 846-853. https://doi.org/10.1016/j.ufug.2014.09.009

- Kowe, P., Mutanga, O., Odindi, J., & Dube, T. (2021). Effect of landscape pattern and spatial configuration of vegetation patches on urban warming and cooling in Harare metropolitan city, Zimbabwe. GIScience & Remote Sensing, 58(2), 261-280. https://doi.org/10.1080/15481603.2021.1877008
- Lemoine-Rodríguez, R., Inostroza, L., Falfán, I., & MacGregor-Fors, I. (2022). Too hot to handle? On the cooling capacity of urban green spaces in a Neotropical Mexican city. Urban Forestry & Urban Greening, 74. https://doi.org/10.1016/j.ufug.2022.127633
- Li, B., Shi, X., Wang, H., & Qin, M. (2020). Analysis of the relationship between urban landscape patterns and thermal environment: a case study of Zhengzhou City, China. *Environ Monit Assess*, 192(8), 540. https://doi.org/10.1007/s10661-020-08505-w
- Li, B., Wang, W., Bai, L., Wang, W., & Chen, N. (2018). Effects of spatio-temporal landscape patterns on land surface temperature: a case study of Xi'an city, China. *Environ Monit Assess*, 190(7), 419. https://doi.org/10.1007/s10661-018-6787-z
- Li, C., Lu, L., Fu, Z., Sun, R., Pan, L., Han, L., Guo, H., & Li, Q. (2022). Diverse cooling effects of green space on urban heat island in tropical megacities. *Frontiers in Environmental Science*, 10. https://doi.org/10.3389/fenvs.2022.1073914
- Li, J., Song, C., Cao, L., Zhu, F., Meng, X., & Wu, J. (2011). Impacts of landscape structure on surface urban heat islands: A case study of Shanghai, China. *Remote Sensing of Environment*, 115(12), 3249-3263. https://doi.org/10.1016/j.rse.2011.07.008
- Li, T., Cao, J., Xu, M., Wu, Q., & Yao, L. (2020). The influence of urban spatial pattern on land surface temperature for different functional zones. *Landscape and Ecological Engineering*, *16*(3), 249-262. https://doi.org/10.1007/s11355-020-00417-8
- Li, T., Xu, Y., & Yao, L. (2021). Detecting urban landscape factors controlling seasonal land surface temperature: from the perspective of urban function zones. *Environ Sci Pollut Res Int*, 28(30), 41191-41206. https://doi.org/10.1007/s11356-021-13695-y
- Li, X., Kamarianakis, Y., Ouyang, Y., Turner Ii, B. L., & Brazel, A. (2017). On the association between land system architecture and land surface temperatures: Evidence from a Desert Metropolis—Phoenix, Arizona, U.S.A. *Landscape and Urban Planning*, 163, 107-120. https://doi.org/10.1016/j.landurbplan.2017.02.009
- Li, X., Zhou, W., & Ouyang, Z. (2013). Relationship between land surface temperature and spatial pattern of greenspace: What are the effects of spatial resolution? *Landscape and Urban Planning*, 114, 1-8. https://doi.org/10.1016/j.landurbplan.2013.02.005
- Li, X., Zhou, W., Ouyang, Z., Xu, W., & Zheng, H. (2012). Spatial pattern of greenspace affects land surface temperature: evidence from the heavily urbanized Beijing metropolitan area, China. *Landscape Ecology*, 27(6), 887-898. https://doi.org/10.1007/s10980-012-9731-6
- Li, Y., Fan, S., Li, K., Zhang, Y., & Dong, L. (2020). Microclimate in an urban park and its influencing factors: a case study of Tiantan Park in Beijing, China. Urban Ecosystems, 24(4), 767-778. https://doi.org/10.1007/s11252-020-01073-4
- Li, Y., Fan, S., Li, K., Zhang, Y., Kong, L., Xie, Y., & Dong, L. (2021). Large urban parks summertime cool and wet island intensity and its influencing factors in Beijing, China. Urban Forestry & Urban Greening, 65. https://doi.org/10.1016/j.ufug.2021.127375

- Li, Z., Xie, C., Chen, D., Lu, H., & Che, S. (2019). Effects of Land Cover Patterns on Land Surface Temperatures Associated with Land Use Types along Urbanization Gradients in Shanghai, China. *Polish Journal of Environmental Studies*, 29(1), 713-725. https://doi.org/10.15244/pjoes/99974
- Liu, H., & Weng, Q. (2009). Scaling Effect on the Relationship between Landscape Pattern and Land Surface Temperature. *Photogrammetric Engineering & Remote Sensing*, 75(3), 291-304. https://doi.org/10.14358/pers.75.3.291
- Liu, H., & Weng, Q. H. (2009). Scaling Effect on the Relationship between Landscape Pattern and Land Surface Temperature: A Case Study of Indianapolis, United States. *Photogrammetric Engineering and Remote Sensing*, 75(3), 291-304. https://doi.org/Doi 10.14358/Pers.75.3.291
- Liu, J., Zhang, L., Zhang, Q., Zhang, G., & Teng, J. (2021). Predicting the surface urban heat island intensity of future urban green space development using a multi-scenario simulation. *Sustainable Cities and Society*, 66. https://doi.org/10.1016/j.scs.2020.102698
- Liu, K., Li, X., Wang, S., & Gao, X. (2022). Assessing the effects of urban green landscape on urban thermal environment dynamic in a semiarid city by integrated use of airborne data, satellite imagery and land surface model. *International Journal of Applied Earth Observation and Geoinformation*, 107. https://doi.org/10.1016/j.jag.2021.102674
- Liu, K., Su, H., Li, X., Wang, W., Yang, L., & Liang, H. (2016). Quantifying Spatial-Temporal Pattern of Urban Heat Island in Beijing: An Improved Assessment Using Land Surface Temperature (LST) Time Series Observations From LANDSAT, MODIS, and Chinese New Satellite GaoFen-1. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 9(5), 2028-2042. https://doi.org/10.1109/jstars.2015.2513598
- Liu, S., Li, X., Chen, L., Zhao, Q., Zhao, C., Hu, X., & Li, J. (2022). A New Approach to Investigate the Spatially Heterogeneous in the Cooling Effects of Landscape Pattern. *Land*, *11*(2). https://doi.org/10.3390/land11020239
- Liu, W., Jia, B., Li, T., Zhang, Q., & Ma, J. (2022). Correlation Analysis between Urban Green Space and Land Surface Temperature from the Perspective of Spatial Heterogeneity: A Case Study within the Sixth Ring Road of Beijing. *Sustainability*, 14(20). https://doi.org/10.3390/su142013492
- Liu, W., Zhao, H., Sun, S., Xu, X., Huang, T., & Zhu, J. (2022). Green Space Cooling Effect and Contribution to Mitigate Heat Island Effect of Surrounding Communities in Beijing Metropolitan Area. Front Public Health, 10, 870403. https://doi.org/10.3389/fpubh.2022.870403
- Liu, Y., Peng, J., & Wang, Y. (2018a). Application of partial least squares regression in detecting the important landscape indicators determining urban land surface temperature variation. *Landscape Ecology*, 33(7), 1133-1145. https://doi.org/10.1007/s10980-018-0663-7
- Liu, Y., Peng, J., & Wang, Y. (2018b). Efficiency of landscape metrics characterizing urban land surface temperature. *Landscape and Urban Planning*, *180*, 36-53. https://doi.org/10.1016/j.landurbplan.2018.08.006
- Lu, J., Li, C.-d., Yang, Y.-c., Zhang, X.-h., & Jin, M. (2012). Quantitative evaluation of urban park cool island factors in mountain city. *Journal of Central South University*, 19(6), 1657-1662. https://doi.org/10.1007/s11771-012-1189-9
- Lu, L., Weng, Q., Xiao, D., Guo, H., Li, Q., & Hui, W. (2020). Spatiotemporal Variation of Surface Urban Heat Islands in Relation to Land Cover Composition and Configuration: A Multi-Scale Case Study of Xi'an, China. *Remote Sensing*, 12(17). https://doi.org/10.3390/rs12172713

- Lyu, R., Pang, J., Tian, X., Zhao, W., & Zhang, J. (2023). How to optimize the 2D/3D urban thermal environment: Insights derived from UAV LiDAR/multispectral data and multi-source remote sensing data. *Sustainable Cities and Society*, 88. https://doi.org/10.1016/j.scs.2022.104287
- Ma, X., & Peng, S. (2022). Research on the spatiotemporal coupling relationships between land use/land cover compositions or patterns and the surface urban heat island effect. *Environ Sci Pollut Res Int*, 29(26), 39723-39742. https://doi.org/10.1007/s11356-022-18838-3
- Ma, Y., Zhao, M., Li, J., Wang, J., & Hu, L. (2021). Cooling Effect of Different Land Cover Types: A Case Study in Xi'an and Xianyang, China. Sustainability, 13(3). https://doi.org/10.3390/su13031099
- Maimaitiyiming, M., Ghulam, A., Tiyip, T., Pla, F., Latorre-Carmona, P., Halik, Ü., Sawut, M., & Caetano, M. (2014). Effects of green space spatial pattern on land surface temperature: Implications for sustainable urban planning and climate change adaptation. *ISPRS Journal of Photogrammetry and Remote Sensing*, 89, 59-66. https://doi.org/10.1016/j.isprsjprs.2013.12.010
- Masoudi, M., & Tan, P. Y. (2019). Multi-year comparison of the effects of spatial pattern of urban green spaces on urban land surface temperature. *Landscape and Urban Planning*, 184, 44-58. https://doi.org/10.1016/j.landurbplan.2018.10.023
- Masoudi, M., Tan, P. Y., & Fadaei, M. (2021). The effects of land use on spatial pattern of urban green spaces and their cooling ability. *Urban Climate*, *35*. https://doi.org/10.1016/j.uclim.2020.100743
- Masoudi, M., Tan, P. Y., & Liew, S. C. (2019). Multi-city comparison of the relationships between spatial pattern and cooling effect of urban green spaces in four major Asian cities. *Ecological Indicators*, 98, 200-213. https://doi.org/10.1016/j.ecolind.2018.09.058
- Naeem, S., Cao, C., Qazi, W., Zamani, M., Wei, C., Acharya, B., & Rehman, A. (2018). Studying the Association between Green Space Characteristics and Land Surface Temperature for Sustainable Urban Environments: An Analysis of Beijing and Islamabad. *ISPRS International Journal of Geo-Information*, 7(2). https://doi.org/10.3390/ijgi7020038
- Pang, B., Zhao, J., Zhang, J., & Yang, L. (2022). How to plan urban green space in cold regions of China to achieve the best cooling efficiency. *Urban Ecosystems*. https://doi.org/10.1007/s11252-022-01202-1
- Park, J.-H., & Cho, G.-H. (2016). Examining the Association between Physical Characteristics of Green Space and Land Surface Temperature: A Case Study of Ulsan, Korea. Sustainability, 8(8). https://doi.org/10.3390/su8080777
- Peng, J., Dan, Y., Qiao, R., Liu, Y., Dong, J., & Wu, J. (2021). How to quantify the cooling effect of urban parks? Linking maximum and accumulation perspectives. *Remote Sensing of Environment*, 252. https://doi.org/10.1016/j.rse.2020.112135
- Peng, J., Jia, J., Liu, Y., Li, H., & Wu, J. (2018). Seasonal contrast of the dominant factors for spatial distribution of land surface temperature in urban areas. *Remote Sensing of Environment*, 215, 255-267. https://doi.org/10.1016/j.rse.2018.06.010
- Peng, J., Xie, P., Liu, Y., & Ma, J. (2016). Urban thermal environment dynamics and associated landscape pattern factors: A case study in the Beijing metropolitan region. *Remote Sensing of Environment*, 173, 145-155. https://doi.org/10.1016/j.rse.2015.11.027
- Pramanik, S., & Punia, M. (2019). Assessment of green space cooling effects in dense urban landscape: a case study of Delhi, India. *Modeling Earth Systems and Environment*, 5(3), 867-884. https://doi.org/10.1007/s40808-019-00573-3

- Qian, Y., Zhou, W., Hu, X., & Fu, F. (2018). The Heterogeneity of Air Temperature in Urban Residential Neighborhoods and Its Relationship with the Surrounding Greenspace. *Remote Sensing*, 10(6). https://doi.org/10.3390/rs10060965
- Qiu, K., & Jia, B. (2020). The roles of landscape both inside the park and the surroundings in park cooling effect. *Sustainable Cities and Society*, 52. https://doi.org/10.1016/j.scs.2019.101864
- Rahimi, E., Barghjelveh, S., & Dong, P. (2021). Quantifying how urban landscape heterogeneity affects land surface temperature at multiple scales. *Journal of Ecology and Environment*, 45(1). https://doi.org/10.1186/s41610-021-00203-z
- Rakoto, P. Y., Deilami, K., Hurley, J., Amati, M., & Sun, Q. (2021). Revisiting the cooling effects of urban greening: Planning implications of vegetation types and spatial configuration. *Urban Forestry & Urban Greening*, 64. https://doi.org/10.1016/j.ufug.2021.127266
- Ren, Z., He, X., Zheng, H., Zhang, D., Yu, X., Shen, G., & Guo, R. (2013). Estimation of the Relationship between Urban Park Characteristics and Park Cool Island Intensity by Remote Sensing Data and Field Measurement. *Forests*, 4(4), 868-886. https://doi.org/10.3390/f4040868
- Ren, Z., Zheng, H., He, X., Dan, Z., & Xingyang, Y. (2014). Estimation of the Relationship Between Urban Vegetation Configuration and Land Surface Temperature with Remote Sensing. *Journal of the Indian Society of Remote Sensing*, 43(1), 89-100. https://doi.org/10.1007/s12524-014-0373-9
- Rhee, J., Park, S., & Lu, Z. (2014). Relationship between land cover patterns and surface temperature in urban areas. GIScience & Remote Sensing, 51(5), 521-536. https://doi.org/10.1080/15481603.2014.964455
- Rouhi, H., Chamani, N., Jafarnezhad, J., & Asgarian, A. (2018). Spatial assessment of the effects of in situ and neighbourhood factors on urban land surface temperature mitigation in a rapidly developing region. *International Journal of Urban Sustainable Development*, 10(3), 292-304. https://doi.org/10.1080/19463138.2018.1522320
- Shah, A., Garg, A., & Mishra, V. (2021). Quantifying the local cooling effects of urban green spaces: Evidence from Bengaluru, India. *Landscape and Urban Planning*, 209. https://doi.org/10.1016/j.landurbplan.2021.104043
- Shaker, R. R., Altman, Y., Deng, C., Vaz, E., & Forsythe, K. W. (2019). Investigating urban heat island through spatial analysis of New York City streetscapes. *Journal of Cleaner Production*, 233, 972-992. https://doi.org/10.1016/j.jclepro.2019.05.389
- Shi, Y., & Zhao, S. (2022). Discover the desirable landscape structure for mitigating urban heat: The urban-rural gradient approach for an ancient Chinese city. *Cities*, *127*. https://doi.org/10.1016/j.cities.2022.103737
- Shih, W.-y. (2016). The cooling effect of green infrastructure on surrounding built environments in a sub-tropical climate: a case study in Taipei metropolis. *Landscape Research*, 42(5), 558-573. https://doi.org/10.1080/01426397.2016.1235684
- Shih, W. Y. (2017). Greenspace patterns and the mitigation of land surface temperature in Taipei metropolis. *Habitat International*, 60, 69-80. https://doi.org/10.1016/j.habitatint.2016.12.006
- Simwanda, M., Ranagalage, M., Estoque, R. C., & Murayama, Y. (2019). Spatial Analysis of Surface Urban Heat Islands in Four Rapidly Growing African Cities. *Remote Sensing*, *11*(14). https://doi.org/10.3390/rs11141645
- Song, Y., Song, X., & Shao, G. (2020). Effects of Green Space Patterns on Urban Thermal Environment at Multiple Spatial–Temporal Scales. *Sustainability*, 12(17). https://doi.org/10.3390/su12176850
- Sun, X., Tan, X., Chen, K., Song, S., Zhu, X., & Hou, D. (2020). Quantifying landscape-metrics impacts on urban green-spaces and water-bodies cooling effect: The study of Nanjing, China. Urban Forestry & Urban

Greening, 55. https://doi.org/10.1016/j.ufug.2020.126838

- Sun, Y., Gao, C., Li, J., Gao, M., & Ma, R. (2021). Assessing the cooling efficiency of urban parks using data envelopment analysis and remote sensing data. *Theoretical and Applied Climatology*, 145(3-4), 903-916. https://doi.org/10.1007/s00704-021-03665-2
- Sun, Z., Li, Z., & Zhong, J. (2022). Analysis of the Impact of Landscape Patterns on Urban Heat Islands: A Case Study of Chengdu, China. Int J Environ Res Public Health, 19(20). https://doi.org/10.3390/ijerph192013297
- Tan, M., & Li, X. (2013). Integrated assessment of the cool island intensity of green spaces in the mega city of Beijing. International Journal of Remote Sensing, 34(8), 3028-3043. https://doi.org/10.1080/01431161.2012.757377
- Tan, X., Sun, X., Huang, C., Yuan, Y., & Hou, D. (2021). Comparison of cooling effect between green space and water body. Sustainable Cities and Society, 67. https://doi.org/10.1016/j.scs.2021.102711
- Tang, L., Zhan, Q., Fan, Y., Liu, H., & Fan, Z. (2023). Exploring the impacts of greenspace spatial patterns on land surface temperature across different urban functional zones: A case study in Wuhan metropolitan area, China. *Ecological Indicators*, 146. https://doi.org/10.1016/j.ecolind.2022.109787
- Terfa, B. K., Chen, N., Zhang, X., & Niyogi, D. (2020). Spatial Configuration and Extent Explains the Urban Heat Mitigation Potential due to Green Spaces: Analysis over Addis Ababa, Ethiopia. *Remote Sensing*, 12(18). https://doi.org/10.3390/rs12182876
- Vaz Monteiro, M., Doick, K. J., Handley, P., & Peace, A. (2016). The impact of greenspace size on the extent of local nocturnal air temperature cooling in London. Urban Forestry & Urban Greening, 16, 160-169. https://doi.org/10.1016/j.ufug.2016.02.008
- Wang, J., & Zhou, W. (2022). More urban greenspace, lower temperature? Moving beyond net change in greenspace. Agricultural and Forest Meteorology, 322. https://doi.org/10.1016/j.agrformet.2022.109021
- Wang, J., Zhou, W., Zheng, Z., Jiao, M., & Qian, Y. (2023). Interactions among spatial configuration aspects of urban tree canopy significantly affect its cooling effects. *Sci Total Environ*, 864, 160929. https://doi.org/10.1016/j.scitotenv.2022.160929
- Wang, L., Hou, H., & Weng, J. (2020). Ordinary least squares modelling of urban heat island intensity based on landscape composition and configuration: A comparative study among three megacities along the Yangtze River. Sustainable Cities and Society, 62. https://doi.org/10.1016/j.scs.2020.102381
- Wang, T., Tu, H., Min, B., Li, Z., Li, X., & You, Q. (2022). The Mitigation Effect of Park Landscape on Thermal Environment in Shanghai City Based on Remote Sensing Retrieval Method. *Int J Environ Res Public Health*, 19(5). https://doi.org/10.3390/ijerph19052949
- Wang, X., Cheng, H., Xi, J., Yang, G., & Zhao, Y. (2018). Relationship between Park Composition, Vegetation Characteristics and Cool Island Effect. Sustainability, 10(3). https://doi.org/10.3390/su10030587
- Wang, X., Meng, Q., Zhang, L., & Hu, D. (2021). Evaluation of urban green space in terms of thermal environmental benefits using geographical detector analysis. *International Journal of Applied Earth Observation and Geoinformation*, 105. https://doi.org/10.1016/j.jag.2021.102610
- Wang, Y., Huang, J., Chen, C., Shen, J., & Sheng, S. (2021). The Cooling Intensity Dependent on Landscape Complexity of Green Infrastructure in the Metropolitan Area. *Journal of Environmental Engineering and Landscape Management*, 29(3), 318-336. https://doi.org/10.3846/jeelm.2021.15573
- Weber, N., Haase, D., & Franck, U. (2014). Zooming into temperature conditions in the city of Leipzig: how do urban built and green structures influence earth surface temperatures in the city? *Sci Total Environ*, 496, 289-298. https://doi.org/10.1016/j.scitotenv.2014.06.144

- Wen, X., Yang, X., & Hu, G. (2011). Relationship Between Land Cover Ratio and Urban Heat Island from Remote Sensing and Automatic Weather Stations Data. *Journal of the Indian Society of Remote Sensing*, 39(2), 193-201. https://doi.org/10.1007/s12524-011-0076-4
- Wesley, E. J., & A. Brunsell, N. A. (2019). Greenspace Pattern and the Surface Urban Heat Island: A Biophysically-Based Approach to Investigating the Effects of Urban Landscape Configuration. *Remote Sensing*, 11(19). https://doi.org/10.3390/rs11192322
- Wu, C., Li, J., Wang, C., Song, C., Haase, D., Breuste, J., & Finka, M. (2021). Estimating the Cooling Effect of Pocket Green Space in High Density Urban Areas in Shanghai, China. *Frontiers in Environmental Science*, 9. https://doi.org/10.3389/fenvs.2021.657969
- Wu, H., Ye, L.-P., Shi, W.-Z., & Clarke, K. C. (2014). Assessing the effects of land use spatial structure on urban heat islands using HJ-1B remote sensing imagery in Wuhan, China. *International Journal of Applied Earth Observation and Geoinformation*, 32, 67-78. https://doi.org/10.1016/j.jag.2014.03.019
- Wu, Q., Li, Z., Yang, C., Li, H., Gong, L., & Guo, F. (2022). On the Scale Effect of Relationship Identification between Land Surface Temperature and 3D Landscape Pattern: The Application of Random Forest. *Remote Sensing*, 14(2). https://doi.org/10.3390/rs14020279
- Wu, Q., Tan, J., Guo, F., Li, H., & Chen, S. (2019). Multi-Scale Relationship between Land Surface Temperature and Landscape Pattern Based on Wavelet Coherence: The Case of Metropolitan Beijing, China. *Remote Sensing*, 11(24). https://doi.org/10.3390/rs11243021
- Wu, W.-B., Yu, Z.-W., Ma, J., & Zhao, B. (2022). Quantifying the influence of 2D and 3D urban morphology on the thermal environment across climatic zones. *Landscape and Urban Planning*, 226. https://doi.org/10.1016/j.landurbplan.2022.104499
- Wu, Y., Hou, H., Wang, R., Murayama, Y., Wang, L., & Hu, T. (2022). Effects of landscape patterns on the morphological evolution of surface urban heat island in Hangzhou during 2000 – 2020. Sustainable Cities and Society, 79. https://doi.org/10.1016/j.scs.2022.103717
- Wu, Z., & Zhang, Y. (2018). Spatial Variation of Urban Thermal Environment and Its Relation to Green Space Patterns: Implication to Sustainable Landscape Planning. *Sustainability*, 10(7). https://doi.org/10.3390/su10072249
- Xie, M., Chen, J., Zhang, Q., Li, H., Fu, M., & Breuste, J. (2020). Dominant landscape indicators and their dominant areas influencing urban thermal environment based on structural equation model. *Ecological Indicators*, 111. https://doi.org/10.1016/j.ecolind.2019.105992
- Xie, M., Wang, Y., Chang, Q., Fu, M., & Ye, M. (2013). Assessment of landscape patterns affecting land surface temperature in different biophysical gradients in Shenzhen, China. Urban Ecosystems, 16(4), 871-886. https://doi.org/10.1007/s11252-013-0325-0
- Xu, X., Cai, H., Qiao, Z., Wang, L., Jin, C., Ge, Y., Wang, L., & Xu, F. (2017). Impacts of park landscape structure on thermal environment using QuickBird and Landsat images. *Chinese Geographical Science*, 27(5), 818-826. https://doi.org/10.1007/s11769-017-0910-x
- Yan, J., Zhou, W., & Jenerette, G. D. (2019). Testing an energy exchange and microclimate cooling hypothesis for the effect of vegetation configuration on urban heat. *Agricultural and Forest Meteorology*, 279. https://doi.org/10.1016/j.agrformet.2019.107666
- Yan, L., Jia, W., & Zhao, S. (2021). The Cooling Effect of Urban Green Spaces in Metacities: A Case Study of Beijing, China's Capital. *Remote Sensing*, 13(22). https://doi.org/10.3390/rs13224601
- Yang, C., He, X., Wang, R., Yan, F., Yu, L., Bu, K., Yang, J., Chang, L., & Zhang, S. (2017). The Effect of Urban

Green Spaces on the Urban Thermal Environment and Its Seasonal Variations. *Forests*, 8(5). https://doi.org/10.3390/f8050153

- Yang, C., He, X., Yu, L., Yang, J., Yan, F., Bu, K., Chang, L., & Zhang, S. (2017). The Cooling Effect of Urban Parks and Its Monthly Variations in a Snow Climate City. *Remote Sensing*, 9(10). https://doi.org/10.3390/rs9101066
- Yang, C., Zhu, W., Sun, J., Xu, X., Wang, R., Lu, Y., Zhang, S., & Zhou, W. (2021). Assessing the effects of 2D/3D urban morphology on the 3D urban thermal environment by using multi-source remote sensing data and UAV measurements: A case study of the snow-climate city of Changchun, China. *Journal of Cleaner Production*, 321. https://doi.org/10.1016/j.jclepro.2021.128956
- Yang, G., Yu, Z., Jørgensen, G., & Vejre, H. (2020). How can urban blue-green space be planned for climate adaption in high-latitude cities? A seasonal perspective. Sustainable Cities and Society, 53. https://doi.org/10.1016/j.scs.2019.101932
- Yang, L., Yu, K., Ai, J., Liu, Y., Lin, L., Lin, L., & Liu, J. (2021). The Influence of Green Space Patterns on Land Surface Temperature in Different Seasons: A Case Study of Fuzhou City, China. *Remote Sensing*, 13(24). https://doi.org/10.3390/rs13245114
- Yang, L., Yu, K., Ai, J., Liu, Y., Yang, W., & Liu, J. (2022). Dominant Factors and Spatial Heterogeneity of Land Surface Temperatures in Urban Areas: A Case Study in Fuzhou, China. *Remote Sensing*, 14(5). https://doi.org/10.3390/rs14051266
- Yao, L., Li, T., Xu, M., & Xu, Y. (2020). How the landscape features of urban green space impact seasonal land surface temperatures at a city-block-scale: An urban heat island study in Beijing, China. Urban Forestry & Urban Greening, 52. https://doi.org/10.1016/j.ufug.2020.126704
- Ye, H., Li, Z., Zhang, N., Leng, X., Meng, D., Zheng, J., & Li, Y. (2021). Variations in the Effects of Landscape Patterns on the Urban Thermal Environment during Rapid Urbanization (1990–2020) in Megacities. *Remote* Sensing, 13(17). https://doi.org/10.3390/rs13173415
- Yin, J., Wu, X., Shen, M., Zhang, X., Zhu, C., Xiang, H., Shi, C., Guo, Z., & Li, C. (2019). Impact of urban greenspace spatial pattern on land surface temperature: a case study in Beijing metropolitan area, China. *Landscape Ecology*, 34(12), 2949-2961. https://doi.org/10.1007/s10980-019-00932-6
- Yu, S., Chen, Z., Yu, B., Wang, L., Wu, B., Wu, J., & Zhao, F. (2020). Exploring the relationship between 2D/3D landscape pattern and land surface temperature based on explainable eXtreme Gradient Boosting tree: A case study of Shanghai, China. *Sci Total Environ*, 725, 138229. https://doi.org/10.1016/j.scitotenv.2020.138229
- Yu, Z., Guo, X., Jørgensen, G., & Vejre, H. (2017). How can urban green spaces be planned for climate adaptation in subtropical cities? *Ecological Indicators*, 82, 152-162. https://doi.org/10.1016/j.ecolind.2017.07.002
- Yuan, B., Zhou, L., Dang, X., Sun, D., Hu, F., & Mu, H. (2021). Separate and combined effects of 3D building features and urban green space on land surface temperature. *J Environ Manage*, 295, 113116. https://doi.org/10.1016/j.jenvman.2021.113116
- Zawadzka, J. E., Harris, J. A., & Corstanje, R. (2020). A simple method for determination of fine resolution urban form patterns with distinct thermal properties using class-level landscape metrics. *Landscape Ecology*, 36(7), 1863-1876. https://doi.org/10.1007/s10980-020-01156-9
- Zawadzka, J. E., Harris, J. A., & Corstanje, R. (2021). The importance of spatial configuration of neighbouring land cover for explanation of surface temperature of individual patches in urban landscapes. *Landscape Ecology*, 36(11), 3117-3136. https://doi.org/10.1007/s10980-021-01302-x
- Zeng, P., Sun, F., Liu, Y., Tian, T., Wu, J., Dong, Q., Peng, S., & Che, Y. (2022). The influence of the landscape pattern

on the urban land surface temperature varies with the ratio of land components: Insights from 2D/3D building/vegetation metrics. *Sustainable Cities and Society*, 78. https://doi.org/10.1016/j.scs.2021.103599

- Zhang, H., Zhao, X., Kang, M.-y., & Han, J.-j. (2022). Contrasting changes in fine-scale land use structure and summertime thermal environment in downtown Shanghai. Sustainable Cities and Society, 83. https://doi.org/10.1016/j.scs.2022.103965
- Zhang, L., Shi, X., & Chang, Q. (2022). Exploring Adaptive UHI Mitigation Solutions by Spatial Heterogeneity of Land Surface Temperature and Its Relationship to Urban Morphology in Historical Downtown Blocks, Beijing. Land, 11(4). https://doi.org/10.3390/land11040544
- Zhang, M., Zhang, F., Chen, D., Tan, M. L., & Chan, N. W. (2022). Urban local surface temperature prediction using the urban gray-green space landscape and vegetation indices. *Building and Environment*, 226. https://doi.org/10.1016/j.buildenv.2022.109723
- Zhang, X., Zhong, T., Feng, X., & Wang, K. (2009). Estimation of the relationship between vegetation patches and urban land surface temperature with remote sensing. *International Journal of Remote Sensing*, 30(8), 2105-2118. https://doi.org/10.1080/01431160802549252
- Zhang, Y., Wang, Y., & Ding, N. (2022). Spatial Effects of Landscape Patterns of Urban Patches with Different Vegetation Fractions on Urban Thermal Environment. *Remote Sensing*, 14(22). https://doi.org/10.3390/rs14225684
- Zhao, H., Tan, J., Ren, Z., & Wang, Z. (2020). Spatiotemporal Characteristics of Urban Surface Temperature and Its Relationship with Landscape Metrics and Vegetation Cover in Rapid Urbanization Region. *Complexity*, 2020, 1-12. https://doi.org/10.1155/2020/7892362
- Zhou, G., Wang, H., Chen, W., Zhang, G., Luo, Q., & Jia, B. (2019). Impacts of Urban land surface temperature on tract landscape pattern, physical and social variables. *International Journal of Remote Sensing*, 41(2), 683-703. https://doi.org/10.1080/01431161.2019.1646939
- Zhou, L., Hu, F., Wang, B., Wei, C., Sun, D., & Wang, S. (2022). Relationship between urban landscape structure and land surface temperature: Spatial hierarchy and interaction effects. *Sustainable Cities and Society*, 80. https://doi.org/10.1016/j.scs.2022.103795
- Zhou, W., & Cao, F. (2020). Effects of changing spatial extent on the relationship between urban forest patterns and land surface temperature. *Ecological Indicators*, *109*. https://doi.org/10.1016/j.ecolind.2019.105778
- Zhou, W., Cao, F., & Wang, G. (2019). Effects of Spatial Pattern of Forest Vegetation on Urban Cooling in a Compact Megacity. *Forests*, 10(3). https://doi.org/10.3390/f10030282
- Zhou, W., Huang, G., & Cadenasso, M. L. (2011). Does spatial configuration matter? Understanding the effects of land cover pattern on land surface temperature in urban landscapes. *Landscape and Urban Planning*, 102(1), 54-63. https://doi.org/10.1016/j.landurbplan.2011.03.009
- Zhou, W., Shen, X., Cao, F., & Sun, Y. (2019). Effects of Area and Shape of Greenspace on Urban Cooling in Nanjing, China. Journal of Urban Planning and Development, 145(4). https://doi.org/10.1061/(asce)up.1943-5444.0000520
- Zhou, W., Wang, J., & Cadenasso, M. L. (2017). Effects of the spatial configuration of trees on urban heat mitigation: A comparative study. *Remote Sensing of Environment*, 195, 1-12. https://doi.org/10.1016/j.rse.2017.03.043
- Zhou, W., Yu, W., & Wu, T. (2022). An alternative method of developing landscape strategies for urban cooling: A threshold-based perspective. *Landscape and Urban Planning*, 225. https://doi.org/10.1016/j.landurbplan.2022.104449

Zhu, W., Sun, J., Yang, C., Liu, M., Xu, X., & Ji, C. (2021). How to Measure the Urban Park Cooling Island? A Perspective of Absolute and Relative Indicators Using Remote Sensing and Buffer Analysis. *Remote Sensing*, 13(16). https://doi.org/10.3390/rs13163154